ESSD-2019-189, Exposure data for global physical risk assessment

Author comment

We would like to thank the two anonymous referees for their thorough review and the supportive comments, questions and recommendations regarding the manuscript.

On the following pages, please find the comments of both reviewers, the author responses and revisions to the text as realised in the revised manuscript.

Page and line numbers in the revised manuscript are indicates in square brackets: e.g. [p.2, L.22]

Responses to RC1 by Anonymous Referee #1:

1.0.

Data easy to find and easy to use. Very good metadata, clear licensing. The authors have done a good job of making their codes accessible as well as easy to understand and use.

The authors have not, and can not, validate LitPop to exposure. They have no actual global physical asset data to validate against, at least not at higher spatial resolution than country? They make an interesting case of relevance to GDP (or - if data available - to GRP) but not a definitive case. If they have done careful work to produce a trustworthy product - as I believe they have - perhaps they need substantial caution in extrapolating consistency and predictive skill to global scales. The tool sort of works for 14 rich countries for GDP. As exposure examples they show only 4 cities. Extrapolation to a global exposure data product remains very much a work in progress. The skillful combination of night light data and population data, as reproduced here, represents a useful but still small step? This statement (from the discussion section, line 305): “top-down approach implemented here does not account for differences in infrastructure types and vulnerability” seems to this reviewer to represent a more accurate and honest statement than their expansive title. Recommend publication after a better statement of actual accomplishment / progress.

Response: We would like to thank the anonymous reviewer for the positive comments as well as for the questions and suggestions for improvements of the paper. In the following, we would like to respond to the single aspects mentioned above, like the issue of validation and the need for a clearer communication of the actual accomplishments and limitations of the generic methodology for global asset exposure disaggregation presented in our publication.

The objection to the claim for “validation” is well conceived. We agree that the term suggests a more direct evaluation of asset value disaggregation than what we can provide. What we are in fact doing, is to use the related socio-economic flow variable GDP for an evaluation of the LitPop disaggregation approach, comparing a variety of exponent combinations, i.e. changing *m* and *n* in Lit^mPop^n (see also our detailed reply to comments 1.10 and 2.14).

Following both reviewers' concerns regarding the claim of validation, we will rename "validation" to "evaluation" and revise the manuscript in various places in order to communicate and discuss the limitations and the purpose of the evaluation in a more accurate way.

Besides the lack of rigorous validation for stated reasons, the evaluation provides confidence that the disaggregation of national asset values proportionally both to nightlight intensity (Lit) and population count (Pop) enables us to provide a first-order estimation of gridded global asset exposure that mitigates some limitations of using Lit or Pop alone (i.e. blooming, saturation and lack of resolution as discussed in the paper).

Already in the first submitted version of the manuscript, it is stated that the LitPop method was not evaluated for developing countries, and not evaluated against physical asset values but with GDP alone. In line with reviewers' requests, we have strengthened these messages in the revised paper, including parts of the Discussion, too. Additionally, we did strengthen our call for validation against local empirical data to increase confidence, especially before using the data set in developing countries. The specific changes in the discussion can be found in the responses to the specific comments below (c.f. comments 1.15-1.17)

We did indeed pick up the recommendation for a better statement of actual accomplishment and limitations. We have more precisely stated the limitations in the Discussion, but did also include a clearer statement on usability to avoid misunderstandings. In the following, we give an overview of the most relevant changes in response to this. Please note that this general comment also informs changes in other part of the text, that were further revised in response to specific comments of both reviewers, and to the second reviewer's call for mature revisions to improve readability (comment 2.0). Revisions to the text are thus reported in response to the specific comments.

- Revisions in the abstract with regards to the validation/evaluation [p.1, L.12ff]:

  Old: *"To evaluate the predictive skill of the downscaling approach, GDP distributed proportional to LitPop to subnational administrative regions is compared to reference values. The results for 14 countries show that the predictive skill of LitPop is higher than using nightlights or population data alone."*

  Revised: *"Due to the lack of reported subnational asset data, the disaggregation methodology cannot be validated for asset values. Therefore, we compare disaggregated GDP per subnational administrative region to reported gross regional product (GRP) values for evaluation. The comparison for 14 industrialized and new-industrialized countries shows that the disaggregation skill for GDP using nightlights or population data alone is not as high as using a combination of both data types."*

- Renaming of subsections related to the validation/ evaluation as follows: *"2.7 Validation of the Downscaling"* → *"2.6 Evaluation"*; *"3.2 Validation"* → *"3.2 Evaluation"*.
- Additionally, the term of "validation" is replaced by "evaluation" in other parts of the manuscript and further clarifications are added. For instance, the following explanation is added in the Data and Methods Section, in the subsection now named "2.6 Evaluation" [p.7, L.217ff]: *"The LitPop approach's skill in disaggregating asset exposure cannot be evaluated directly due to the lack of reference asset value data on a subnational level. Therefore, GDP and GRP are used instead for an*

indirect evaluation of the methodology. GDP and GRP are used to assess the subnational disaggregation skill, comparing varying combinations of the exponents m and n in $Lit^m Pop^n$."

- *… and further discussed in the Discussion and the Conclusion of the revised manuscript:*

  Discussion [p.14, L.353ff]: *"For the gridded exposure dataset presented here, the LitPop methodology is used to disaggregate total asset values. Due to a lack of subnational reference asset values, the LitPop methodology's performance for the downscaling of asset stock values could not be evaluated directly. The assessment of disaggregation skill was instead based on the flow variables GDP and GRP. Given a correlation between stocks and flows within each country, this approach represents an indirect evaluation of the methodology for asset exposure downscaling."* (c.f. comment 1.8)

  Conclusion [p.14, L.418ff]: *"However, the methodology could not be evaluated directly against subnational asset data and the evaluation based on GDP was limited to 14 OECD countries. Therefore, the asset exposure data is not suitable for applications with a local or sector-specific focus without further validation."*

Specific comments:

1.1. Line 46: "With global satellite images being publicly available and updated regularly, it has been proven to be an useful source". Awkward. Authors intend singular 'it' to refer to nightlight data but in this sentence they confuse readers by the plural reference to satellite 'images'. They could clarify by writing 'global nightlight images' ..., 'they' have proven ...? Need some change to smooth this out.

Response: We revised the sentence according to the reviewer's suggestion (new version in *blue*) [p. 2, L.53]:

"Being publicly available and updated regularly, global nightlight images have been proven to be a useful source […]"

1.2. Line 55: Reader will find no Zhao et al. 2017 reference. Later (line 141) reader encounters "Naizhuo Zhao et al., 2017" with a matching citation in the reference list. Please fix one or the other and then use consistently? Again at line 161. Please check throughout the manuscript, you do not want to get this particular reference wrong.

Response: We have corrected for the faulty reference. The particular publication is now referenced as *Zhao et al. (2017)* throughout the manuscript.

1.3. Line 85: NASA produces the VIRS nightlight product used here but technically the data come from the Suomi NPP's Visible Infrared Imaging Radiometer Suite where NPP indicates a joint NASA NOAA effort. Other ESSD papers that reference nightlight data (for emissions purposes) use the NOAA DMSP URL rather than the NASA VIRS link promoted here? E.g. https://ngdc.noaa.gov/eog/ dmsp/download_radcal.html. Some remote sensing papers compare VIRS to DMSP, favor of VIRS, but gridded emissions products tend to use DMSP? Emissions products tend to want fires but this population product tends to avoid fires? Here (line 89) these authors use the term ‘stable lights’ but most readers will not understand that term as excluding fires? For remote sensing community, some clarification useful here?

Response: We would like to thank for the recommended changes in referencing the Black Marble nightlight product. The nightlights data used for this data set and within all nightlight based modules within the CLIMADA modelling framework is the NASA Earth Observatory as referenced in the manuscript (https://earthobservatory.nasa.gov/features/NightLights/page3.php). To ensure reproducibility, we need to keep the reference to the actual download of the data accurate. The NOAA DMSP URL provided by the reviewer links to an DMSP product and other VIIRS that are not necessarily identical to the Black Marble tiles provided by NASA and used here. According to a study published by Munich Personal RePEc Archive in 2019, “VIIRS night lights data are a better proxy for economic activity than are the more widely used DMSP data.” (Gibson, John and Olivia, Susan and Boe-Gibson, Geua (2019): *Which Night Lights Data Should we Use in Economics, and Where?, https://mpra.ub.uni-muenchen.de/97582/*). The main reasons being that VIIRS signal has less noise and is better suited to pick up dim light sources than DMSP.

In order to clarify the reference, we added the citation, now also referring to the accompanying publication: *Román et al. (2018)*: “NASA's Black Marble nighttime lights product suite” [https://www.sciencedirect.com/science/article/pii/S003442571830110X]. This agrees with Aznar-Siguan and Bresch (2019) who use the same nightlight product (https://www.geosci-model-dev.net/12/3085/2019/)

Temporary fires are not relevant for our use of the nightlight data. They are not part of the stable lights (as clarified below). Sustained and spatially fixed fires, i.e. from industrial burning processes, are likely to contribute to the nightlight intensity in the Black Marble product. This agrees with the purpose of using nightlights as a proxy for human economic activity.

To clarify the term “stable lights”, we now also refer to Román et al. (2018) in Section 2.2 [p.4, L.105f]:

“To isolate luminosity from sustained human activity, the Black Marble nightlight product includes corrections for Lunar artefacts, cloud, terrain, atmospheric, snow, airglow, stray light, and seasonal effects (Carlowicz, 2017; Lee et al., 2014; Román et al., 2018)

(C.f. response to comment 2.3 for for further elaborations on the nightlight data used).

1.4. Line 87: Better to use ISO units for times, e.g. 0130 and 1330?

Response: The notation with “am” and “pm” is indeed not ISO. Thus, we changed the time format in Section 2.2 [p.4, L.104]] to *“01:30”* and “*13:30”* according to ISO 8601. ISO 8601 formats time of the day as follows: hh:mm:ss. Reference: https://www.iso.org/iso-8601-date-and-time-format.html (fee required for access) or for a free overview: https://en.wikipedia.org/wiki/ISO_8601.

1.5. Line 104: “selected for this application, because unlike other spatial population datasets, it does not incorporate” Change punctuation here to: ‘... selected for this application because, unlike other spatial population datasets, it does not incorporate ...’

Response: The punctuation in the cited sentence in Section 2.3 was corrected and "this application" replaced by "the LitPop methodology" to communicate more clearly [p. 4, L.123]:

"[…] selected for the LitPop methodology because, unlike other spatial population datasets, […]"

1.6. Line 108: "both spatial and temporal resolution" You mean temporal overlap or time step coincidence, rather than resolution? Resolution would suggest, annual, monthly, etc., when in fact you have used only 2012 and 2016 for nightlight while GPW has 2010 and 2015? (On line 115 you refer to time steps rather than temporal resolution.)

Response: According to the reviewer's suggestion, we changed the text in Section 2.3 according as follows [p.4, L.127]:

Old: *"[…], in terms of both spatial and temporal resolution."*

Revised: *"[…], both in terms of spatial resolution and available time steps."*

1.7. Line 118, 119: "no direct damage to the value of the land itself in the case of disaster" Authors need to justify this default assumption. For coastal land masses subject to wind, water current and sea level/inundation damage, land values almost certainly change pre- to post-disaster, sometimes extensively. For example, termination or increased cost of flood zone insurance, as does and even more should happen post- storm, changes land values? Local governments and commercial real estate firms notorious for artificially maintaining land-values at pre-storm levels to thereby maintain tax bases and market values? Hurricane loss and damage community publishes many assessments on land values before and after storm landfall?

Response: We agree with the reviewer, that there are scenarios in which natural hazard affects the value of land. At the same time, the data set focuses on tangible / physical assets. Just as cultural or emotional values exposed to disasters are not considered, we also exclude the value of the land itself. Since the mark-up of 24% is a simple multiplicative factor in the produced capital accounts, land value can be included by users of the data set by multiplying all values with the factor 1.24. For clarification, we added the following two sentences in Section 2.4.1 [p.4, L.136ff]:

"While not universally true, this assumption is based on the focus of the asset exposure data for the purpose of assessing direct impact to tangible structures. For applications considering the impact on the value of land, the linear scale-up can be reapplied before utilization of the asset exposure data."

1.8. Line. 120: A substantial literature exists on weakness of national GDP reports as indicators of economic output. Perhaps not relevant here? If relevant, authors need to justify why they use GDP?

Response: Thank you for pointing out the wider discussion on the limitations of GDP. The main reason to use GDP for evaluation is that national GDP data is available globally and sub-national GDP (i.e. GRP) is available for a variety of countries. The reason for this is that GDP is a standard that is used widely in research and outside academia, and thus GDP numbers are provided by many governmental and international agencies. Discussing the pros and cons of using GDP is not the scope of this paper, as it is mainly used for the evaluation of the disaggregation.

In the revised manuscript, we state the limitations that arise by evaluating the downscaling approach with an economic flow variable but applying it to a stock variable in the Discussion of the revised manuscript [p.14, L.353ff]:

"For the gridded exposure dataset presented here, the LitPop methodology is used to disaggregate total asset values. Due to a lack of subnational reference asset values, the LitPop methodology's performance for the downscaling of asset stock values could not be evaluated directly. The assessment of disaggregation skill was instead based on the flow variables GDP and GRP. Given a correlation between stocks and flows within each country, this approach represents an indirect evaluation of the methodology for asset exposure downscaling."

1.9. Line 134: "wide range of income groups and world regions". But, OECD data already filter out a large number of countries/economies? Therefore one might gain a wide range of OECD data, but not actually a wide range of global data? The list of 14 countries presented here looks more like G-7 plus BRIC, e.g. not exactly a wide range of global economies or regions? In line 135 the authors admit "bias towards developed and emerging economies". "wide range" is not correct.

Response: This criticism of the term "wide range" is well taken, as discussed already in response to the general comment 1.0. To clarify this limitation of the selected countries, added the information to the abstract that the 14 countries are all industrialized or newly-industrialized. For further transparency, we changed the sentences in Section 2.4.3 of the revised manuscript as follows (changes in *blue*) [p. 5, L.168ff]:

"The aim of the selection was to include countries from ~~a wide range~~ as wide as possible of income groups and world regions. Since the selection of countries was limited by the availability of GRP data, 135 the selection has a bias towards ~~developed and emerging economies with~~ industrialized and newly industrialized OECD member states. According to World Bank income groups, these countries include eight countries from the high-income group (World Bank income group 4), four countries from the upper-middle-income group (3), two countries from the lower-middle-income (2), and no countries from the low-income group (1)."

1.10. Line 234: What is "*Pop*^{2}"? Earlier we have seen and understood *Lit*^{m}*Pop*^{n} with m and n as weighting factors. In Figure 3 and Table A3 the reader now encounters Lit with values 1 (default) through 5, Pop with values 1 and 2, and LitPop with m of 2 and 3. In plain terms, we see examples with Lit weighted normally to heavily, Pop weighted normally to some increased value, and the LitPop combination with Lit at weights of 3 and 4. One can tease out the meanings and processes but one does not know the weighting factors? Weight of m = 2 means double? 20%? 2 orders of magnitude? It will follow that m = 3 indicates thrice? 30%? three orders of magnitude? From equation (1) m and n look like exponents, so Lit^5 indicates Lit to the 5th, e.g. 5 orders of magnitude? Mathematically correct, one suspects, but meaning obscure. Why did authors choose to vary Lit more than Pop? Given the strong valid preference for LitPop (with m = n = 1) what does a reader learn by seeing all these permutations? In line 279 the authors use the word "multiplicative" but, for this reader, that term differs substantially from exponential? Later (line 290) the authors use the word "exponent". Again, one assumes they know what they did, but they have not conveyed their approach clearly to this reader.

Response: Thank you again for pointing out that there can be confusion about what *m and n* are in the Method and the Results sections of the paper. As stated in line 150 (first submission) in the Methods section 2.5, m and n are the exponents of Lit and Pop respectively. I.e. $Lit^2Pop^1 = Lit*Lit*Pop$ at each grid cell. That's why the combination could also be called multiplicative (c.f. line 279). A high exponent for *Lit* (f.i. Lit^4) does not only mean that *Lit* is weighted more against *Pop* for each pixel, but also that bright pixels (i.e. with large values of *Lit)* are weighted even higher against dim pixels with low values of *Lit* (within the same country).

For a more detailed discussion regarding the exponents, please also refer to our response to comment 2.5.

We will take up this comment by calling m and n 'exponents' more consequently throughout the text. In Section 2.5 of the revised manuscript, we additionally add the following explanation [p.6, L.197-201]:

"Changing the exponents m and n determines with which power the two input variables contribute to the disaggregation function. The exponents m and n do not only weight relatively between Lit and Pop but they also determine the contrast in the distribution between all grid cells within a country. The larger the exponent, the more value is concentrated on grid cells with large values of Lit or Pop respectively. The aim of the evaluation described in Section 2.6 is to compare disaggregation skill of varied combinations of m and n and select the most adequate combinations for subnational disaggregation."

Ad *"Why did authors choose to vary Lit more than Pop?":* The exponent combinations chosen in this publication were derived based on literature and iteration: In previous studies, exposure has been estimated by disaggregation either proportionally to Pop^1 (e.g. Gunasekera et al., 2015) or Lit^m with m>1 to account for the exponential relationship between nightlight intensity and economic indicators as discussed by Zhao et al. (2017) among others (e.g. Aznar-Siguan and Bresch, 2019). Based on this, we varied exponents but stopped when the skill scores are expected to get only worse or stagnate. This is possible because of a monotonous effect of changing the exponent. For instance, from Pop^1 to Pop^2, all three skill scores perform worse. (c.f. Pop^2 in Figure 3a-c).. Considering the drop in performance of Pop^2 compared to Pop^1 with regards to these skill indicators, there is no point in considering higher exponents (i.e. Pop^3, Pop^4). A larger exponent is expected to lead to an even lower performance.

Ad "Given the strong valid preference for LitPop (with m = n = 1) what does a reader learn by seeing all these permutations?": We had no a priori preference for *m = n = 1.* The different combinations of the two exponents were analyzed to find the best performing combination of Lit and Pop. Thus, showing the combinatiions displays the results justifying our choice of $Lit^1 * Pop^1$ over other combinations of *Lit* and *Pop*.

Addressing the comments of both anonymous reviewers concerning the clarity of the disaggregation function, we have rewritten Sections 2.5 / 2.6. In this process, we combined both sections into one section (2.5).

In this process, the mentioning of "*m = n = 1*" as a default was deleted from section 2.6, since suggesting this combination as a "default" is only derived further down and it is rather a choice than a default.

Additionally, we have revised the opening sentences of Section 3.2, providing more details on the evaluation process. The paragraph now reads as follows [p.9, L.273-280]:

"To evaluate the performance of the LitPop methodology, we compute and compare the disaggregation skill in regards to GDP for varying exponents m and n in $Lit^m Pop^n$ *(Eq. 1 and 2). Here, we show the comparison based on 14 countries with a total of 507 regional GRP data points available and ten combinations of m and n:* Lit^1Pop^1, Lit^1, Lit^2, Lit^3, Lit^4, Lit^5, Pop^1, Pop^2, Lit^2Pop^1, *and* Lit^3Pop^1. *These exponent combinations were selected based on examples in the literature and then explored iteratively, stopping at combinations with decreased skill compared to lower order combinations. The 14 countries make up 67% (USD 168 trillion) of the total dataset's exposure and 64.5% (USD 52 trillion) of global GDP in 2014. For each country and exponent combination, the median and the spread of three skill metrics are compared:* ρ, β, *and RMSF (Fig. 3 and Tables A2 and A3).*

1.11. Line 240: "is the most an adequate combination"

Response: We corrected the typo in Section 3.2, removing "an": [p.10, L.299]

Revision: *"the most ~~an~~ adequate combination"*

1.12. Line 243: "In the validation in Section 3.2, Mexico shows" Because the authors do not mention Mexico in Section 3.2, this sentence should instead read 'Compared to' or 'In contrast to'?

Response: The reference to Section 3.2 is indeed not precise. The low correlation coefficients are not shown directly in Section 3.2 but in Table A2a in the Appendix (column labeled MEX). Please note that we have rearranged the results section in response to the second reviewer's call for more clarification. We have adjusted the text to clarify the reference. New opening paragraph in the revised manuscript (including changes in response to other comments): [p.12, L.321-327]

"The skill metrics for the subnational disaggregation of GDP in the country Mexico shows low value of ρ *compared to most other countries for all tested values of m and n* (ρ=0.76 *for* Lit^1Pop^1, *c.f. Table A2a). The example of Mexico is presented here to illustrate limitations and uncertainties of the disaggregation approach. Figure 5 shows the data behind the evaluation for Mexico, i.e. modelled and reference nGRP for all 32 districts of Mexico. The corresponding plot data can be found in Table S2 as supplementary material. While the LitPop methodology performs well for most of the districts with relatively low GRP, it fails to reproduce reference nGRP for the main (capital) metropolitan region consisting of the districts México and Mexico City (Distrito Federal).*

1.13. Line 245: “the smaller districts” You mean smaller economically, not smaller geographically?

Response: We would like to thank the reviewer for pointing out this ambiguity. Please refer to our response to comment 2.11 by the second reviewer for a more detailed discussion regarding this point.

Revision: we have specified the statement as follows (changes in *blue*): [p.8, L.242; p. 12, L.325; p.13, L.333]

“the ~~smaller~~ districts with relatively low GRP”

1.14. Line 253: “housing and infrastructure in suburban México that is used by a population that works in the city”. This rural or suburban pattern of residence coupled with employment/work in a central district must represent a very common or even predominant pattern in most large cities? E.g. Rio, Jakarta, New York, even Mumbai? Not clear to this reviewer why Mexico City would represent an outlier in this regard?

Response: We agree that this phenomenon is not specific to Mexico City. We chose to show Mexico because the split of the whole Mexico City area into two administrative regions allows us to illustrate this phenomenon with our analysis.

Please note that we have revised the whole section on the example of Mexico in response to comments 1.12-1.14 and especially comment 2.12 by the second reviewer. Please refer to our response to comments 1.12 and 2.12 for a more detailed discussion and a revised version of the Section. [Section 3.4, p.12f]

1.15. Lines 268, 269: “performs well across countries from different continents and income groups” I already questioned this supposed broad coverage (see comment for line 134, above) and authors in their text have admitted that this is not true. Given the OECD filters and limited availability of data, the authors should show much more caution with broad statements like this?

Response: As discussed in the response to the reviewer’s comment 1.0, we are following the rightfully cautioning remarks of the reviewer. Therefore, we have reformulated the claims of performance in Section 4 (Discussion) of the revised manuscript as follows: [p.13f, L.345-352]

Old: *“It should be noted that due to lack of data we were not able to evaluate the method’s performance for low income countries (World Bank income group 1). Therefore, the application of the asset exposure data for local assessments in countries within this income group should be treated with caution. Another caveat to global consistency is the fact that the quality and resolution of the underlying population dataset varies between countries, as discussed in greater detail in the next paragraph. As a consequence of these limitations, asset exposure data should be validated against local data before application for local risk assessments, especially in low income countries.”*

Revised: *“However, the evaluation of the of the methodology’s disaggregation skill presented here is limited to an assessment of disaggregation skill for 14 OECD countries. It should be noted that due to lack of data we were not able to evaluate the method’s performance for low income countries (World Bank income group 1). Therefore, the* *application of the asset exposure data for local assessments in countries within this income group should be treated with caution. Another caveat to global consistency is the fact that the quality and resolution of the underlying population dataset varies between countries, as discussed in greater detail in the next paragraph. As a consequence of these limitations, asset exposure data should be validated against local data before application for local risk assessments, especially in low income countries."*

1.16. Line 268: "Global" consistency. Authors presented data from 14 highly-selected countries. This subsample hardly qualifies as global. We do not even know - at least from this paper - what percentage of global population, global nightlights, or global GDP their subset represents. Substantial, perhaps (at least in 2012 and 2016), but hardly definitive?

Response: Thank you for this helpful remark. We call the data set "globally consistent" because consistent data and methods were applied for all countries. We agree that the evaluation does not provide a global validation of the dataset, however, they do represent around one third of the total global asset exposure. In order to better communicate the global consistency of the data set, we thus provide a world map of the exposure data in the beginning of the revised Results section. In addition, we provide numbers of total GDP, and asset values represented for all countries for which exposure data has been made available, as well as for the 14 countries used for evaluation.

In Section 3.1 ["Global gridded asset exposure", p. 8f] of the revised manuscript, we now provide a world map [Figure 2, p.9] and the following information [p.8f, L.254-260]:

"We applied the LitPop methodology with the exponents m = n = 1 to compute gridded asset exposure data for 224 countries and areas worldwide (Fig. 2). Total physical asset values of 2014 were disaggregated proportionally to Lit^1Pop^1 to a grid with the spatial resolution of 30 arcsec (approximately 1 km). Total asset values in the dataset sum up to $2.51*10^{14}$ (251 trillion) current USD of 2014. The 140 countries with produced capital data used as total asset value, contribute USD 245 trillion (97.6 %) to the total asset exposure. The remaining 84 countries where asset values were estimated from GDP and a GDP-to-wealth ratio instead, contribute the remaining USD 6 trillion. In total, the 224 countries contribute around 99.9% to recorded global GDP."

In Section 3.2, we add the following information ["Evaluation", p.9, L.275f]:

"The 14 countries make up 67% (USD 168 trillion) of the total data set's exposure and 64.5% (USD 52 trillion) of global GDP in 2014."

A brief discussion of this is added in Section 4 [Discussion, p.13, L.343f]:

"While the presented data set is not complete, it provides data for the countries contributing 99.9% of global GDP."

1.17. Line 274: "income group 1" Does this text refer to a World Bank or IPCC categorization? Reader has not encountered group numbers? In lines 136, 137 authors referred to lower-middle-income and low income groups. 'group 1' refers to these income levels? Reader must seek out table legend for Table A1 to learn with group 1 means.

Response: We agree that the income group definition should be stated earlier in the manuscript. We thus revise the manuscript to specify the income group definition (World

Bank income group) in both paragraphs referred to by the reviewer (c.f. response to comment 1.9), changes in *blue*:

Section 2.4.3 (GRP): [p.5, L.171-174]

"According to World Bank income groups, these countries include eight countries from the high-income group (World Bank income group 4), four countries from the upper-middle-income group (3), two countries from the lower-middle-income (2), and no countries from the low-income group (1). ~~The i~~Income groups and data sources per country are listed in Table A1 in the Appendix."

Section 4 (Discussion): [p. 13, L.346f]

"It should be noted that due to lack of data we were not able to evaluate the method's performance for ~~countries in~~ low income countries (World Bank income group 1).

1.18. Line 294: "the LitPop exposure model" by this point in this manuscript, this reader views this phrase with deep dis-satisfaction and suspicion. The authors showed possibly valid (but highly geographically limited) LitPop to GDP correlations but they have in no way advanced to a LitPop to exposure model. As they say themselves!

Response: We agree that the terminology used here was misleading. We have changed the wording in the specified line and others to *"LitPop methodology"*. (C.f. response to comment 2.2. regarding the use of the term LitPop).

1.19. Lines 311 to 319, openness replicability etc. Excellent section! Could / should prove useful example for other ESSD papers.

Response: We would like to thank the reviewer again for pointing this out. This is much appreciated.

Review ESSD-2019-189, global exposure data

Responses to RC2 by Anonymous Referee #2

2.0.

The authors present an open-source method that can be used to downscale low-resolution economic predictors to high-resolution gridded data by using nightlight intensity and gridded population data. The method and required data are described and a validation of the methodology is conducted for 14 selected countries. A global high-resolution dataset for 227 countries is created using this method and openly available for download. The documentation of the method in the open-source archive CLIMADA and the dataset are state-of-the-art and easily assessable to users. The presentation of the method and the dataset within the present manuscript needs major improvements. In general, the method and the dataset are described incompletely, the validation exercise and the subsequent consequences appear ad-hoc and unmotivated. In particular, the manuscript lacks a clear and precise writing style in various locations that make it difficult for the reader to follow. Important information is missing, appears in different locations or is poorly referenced. This is a data description paper so all the relevant information concerning the data (including the input data) should be assembled here. Besides the specific locations noted below I ask the authors to critically revise the full manuscript to improve readability and understanding. I had to (re-)read many parts of the manuscript several times to finally get the full picture.

Response:

We would like to thank the reviewer for the synthesis and the key comment regarding readability, as well as for the detailed suggestions for improvement. In response to the reviewers' general recommendations concerning readability and understanding, as well as the specific comments, we have applied major revisions to the manuscript. They concern the terminology but also the general structure of the Sections Data & Methods and the Results. Most specific changes are found in response to the more specific comments of both reviewers.

For a better reading experience, we introduced a more precise and consistent naming of the methodology as "LitPop" (c.f. comment 2.2). In addition, we are now consequently calling the resulting data "asset exposure data" (c.f. comment 2.17). We also replaced the term "validation" with the more fitting term of "evaluation" (c.f. comment 1.0). The term "disaggregation" is now used more consequently throughout the manuscript to refer for the core process of distributing asset values proportionally the combination of nightlight intensity and population data.

We **rearranged the Results section [p.8-13]** to start with the main result of the publication which is the global asset exposure data set that is available online (Section 3.1). This section now also includes a world map (new Figure 2) to give a quick impression of the data. The plots of disaggregated asset exposure data in metropolitan areas used for a qualitative evaluation of the disaggregation (Figure 4) are moved down below the quantitative evaluation.

We are confident that these and many other revisions in the manuscript included in direct response to the specific comments of the two reviewers help to increase the general readability and strengthen the message of the manuscript, and again want to thank the anonymous reviewers for their useful suggestions.

Please refer to the responses to the more specific comments below for further elaborations and specific revisions.

Major points:

2.1. The manuscript is about a global exposure dataset (for asset and/or GDP exposure?) for 227 countries. However, most of the manuscript deals with validation of the 14 test countries and some metropolitan areas. I expect the authors to include a description of the full dataset in section 3. This should include a clear statement of the countries and time periods included, missing countries or regions with low coverage in the available dataset and maybe even a worldmap figure. The reader should not download the huge dataset or consult Worldbank data in order to obtain this information himself.

Response: In response to this very valid request of the reviewer, we added an overview of all used input data including source and reference year in the new **Table 1**. Structured information and meta data on all countries was previously not provided or only as part of the data repository. Detailed information per country is now presented in Table S1 in the Supplementary Materials. This includes metadata for all 224 countries included in the asset exposure data set and 26 countries and areas not included. In addition, more detail on the total asset value data are now given in the text in Section 2.4.1. During the revision process, we realized that the actual numbers of countries with data provided is 224 and not 227. We would like to apologize for this mistake which is now corrected for in the current version of the manuscript. The three omitted areas that were previously mistakenly included into the list of countries with data are British Indian Ocean Territory, French Southern Territories, and South Georgia.

In response to the comment, we have included more information on data sources and countries in the Sections Data and Methods (Table 1 and Section 2.4.1), Results (Section 3.1), as well in Table S1 in the Supplement.

Addition in Section 2.4.1 of the revised manuscript ("Total asset value per country"): [p.5, L.139-153]

"Out of a total of 250 countries we considered for the production of this dataset, produced capital numbers for 2014 are available for 140 countries. For these 140 countries, produced capital for 2014 was used here as total asset value for disaggregation. For additional 87 countries, total asset values were set to non-financial wealth. Non-financial wealth was computed from the country's GDP and the GDP-to-wealth ratio estimates derived from the Credit Suisse Research Institute's Global Wealth Report (Credit Suisse Research Institute, 2017). This approach has previously been followed by Geiger et al. (2018). We compared produced capital and non-financial wealth for 140 countries (Table S1 in the Supplement) and found that non-financial wealth can be used as a conservative approximation of produced capital. For 59 of the 87 countries without produced capital data, an average GDP-to-wealth ratio of 1.247 was applied. In summary, the whole dataset contains gridded asset exposure data for a total of 224 countries, ignoring 26 countries and areas due to lack of data. Missing countries and areas (with currently assigned ISO 3166-1 alpha-3 codes) are Aland Islands, Antarctica, Bonaire, British Indian Ocean Territory, Sint Eustatius and Saba, Bouvet Island, Cocos (Keeling) Islands, Christmas Island, Guadeloupe, French Guiana, French Southern Territories, Heard Island and McDonald Islands, Holy See, Kosovo, Libya, Martinique, Mayotte, Pitcairn, Palestine, Reunion, South Georgia and the South Sandwich Islands, South Sudan, Svalbard and Jan Mayen, Syrian Arab Republic, Tokelau, United States Minor Outlying Islands, and Western Sahara.

An overview over the utilized data per country, including, produced capital (were available), GDP-to-wealth ratios, and GDP for 2014 is provided in Table S1."

Addition to Section 3.1 ("Global gridded asset exposure"): *Please refer to comment 1.16.*

2.2. The name of the method 'LitPop' and the function 'LitPop' (sometimes in italic) are used as synonyms. This is VERY confusing for the reader. To avoid confusion I would strongly encourage the authors to use LitnPopm (with m and n in the exponent) everytime you talk about the function, even in the case when the exponent is one you should write Lit1Pop1 (with ones in the exponent).

Response: We appreciate the reviewer's feedback concerning the ambiguity of the term "LitPop" in the manuscript. We have revised the terminology throughout the manuscript (including figures and tables) in order to make it more precise and easier to follow for the readers. We revised the terminology based on the suggestions by the reviewer. To go into detail, here are the now consistently used terms and variables used in the revised manuscript, including the key sentences and definitions in the revised manuscript:

The term "LitPop" names the asset exposure disaggregation methodology described and evaluated in the manuscript. Thus, "LitPop" spelled that way signifies neither the resulting data set nor a specific function.

The variable "$Lit^{m}Pop^{n}$" signifies a gridded digital number that is computed per pixel according to Equation 1 (Section 2.5). Briefly said, "$Lit^{m}Pop^{n}$" is computed per pixel by multiplying nightlight intensity to the power of m with population count to the power of n.

The LitPop methodology is not limited to the realization with $Lit^{1}Pop^{1}$. To make this difference clear, the exponents m and n are now always written, even when they are equal to one. Only in cases where an exponent is set to zero, the entire part is omitted, i.e. Lit^{2} instead of $Lit^{2}Pop^{0}$.

Changes in key paragraphs in the manuscript (revised text in *blue*):

- LitPop: [Introduction, p.2, L.73f]

"Here, we are using and expanding the "lit population" approach presented by Zhao et al. (2017) to define and implement a globally consistent methodology for asset exposure disaggregation, named LitPop hereafter."

- $Lit^{m}Pop^{n}$: [Data and Methods, p.6, L.182f]

"In a first step, the two gridded input datasets are interpolated linearly to the same resolution of 30 arcsec~~, or coarser resolution if desired~~. Then, the combination of the two aforementioned datasets is conducted for each ~~pixel~~ grid cell:

$$Lit^{n}Pop^{m}{}_{pix} = \left(NL_{pix} + \delta\right)^{n} \cdot Pop_{pix}{}^{m} \qquad (1)$$

Where the ~~LitPop~~ digital number value $Lit^{m}Pop^{n}_{pix}$ per grid cell (pix) is computed from the grid cell's nightlight intensity $NL_{pix} \in [0, 255]$, ~~and~~ population count $Pop_{pix} \in \mathbb{R}^{+}$, as well as the exponents $n, m \in \mathbb{N}$. For all m > 0, the added δ is equal to 1 to ensure that non-illuminated but populated ~~pixesl~~ grid cells do not get assigned zero value. In the case that nightlight data is used on its own without population data (m = 0), δ is set to 0." (Section 2.5 in Data and Methods)

We have also adjusted the wording in the schematic overview of the methodology (Figure 1) to agree with the revised terminology and moved Figure 1 down to Section 2.5 to make it easier to refer to the figure when reading the technical description of the methodology. [p.7, L.205],

2.3. Although I am not an expert on nightlight data I have the impression that there are some subtleties involved the user should know about. I quick google search tells me that usually an exponent >1 for nightlight data is used when deriving economic proxies to partially deal with the saturation issue. (This is somehow also apparent from your results in Figure 3). What about latitude-dependence of light intensity and the influence on your global dataset? I think the discussion in section 2 on input data needs to be advanced so the reader really gets to know the dataset and its subtleties.

Response:

Regarding the exponent >1 usually used for nightlight data:

Thanks for pointing out that nightlight intensity is usually taken to a power larger than 1 for deriving economic proxies (corresponding to Lit^2, Lit^3, Lit^4, and Lit^5 in the manuscript) The exponential relationship between nightlight intensity and economic activity as it was also pointed out by Zhao et al. (2017) upon which the LitPop methodology is based. As we also discuss in the manuscript with reference to the combination of nightlight intensity with population data is an alternative approach to mitigate the limitations arising from the saturation effect of nightlight data, among others. Indeed, Zhao et al. (2017) discuss empirical evidence for an exponential relationship between nightlight intensity and population density. This relationship makes it more tangible why $Lit^m Pop^n$ has been considered as an alternative downscaling function in the first place. For the evaluation, varying combinations of the exponents m and n are compared precisely for the purpose to decide which exponential combination to use for the production of a global asset exposure data set and to discuss the best alternatives (Sections 2.6 and 3.2 in the revised manuscript). As the reviewer has noted rightly, the disaggregation of GDP to subnational units based on *Lit* alone performs indeed better for m>1 than for m=1. However, in combination with *Pop*, larger exponents m>1 lead to a decrease in skill.

Changes to the manuscript: We have revised the Introduction in response to several comments by the two anonymous reviewers, both to increase readability and include information and references that had been missing before. Among these changes is a more detailed discussion of the use of nightlight data and the approach presented by Zhao et al. (2017). The most crucial revised paragraph regarding above comment is the following:[p.2, L.63-72]

"As a consequence of saturation, socioeconomic indicators scale rather exponentially than linearly with nightlight intensity (Zhao et al., 2015, 2017). To counteract the saturation effect, Aznar-Siguan and Bresch (2019) used squared nightlight intensity as a basis for asset exposure disaggregation. Saturation and blooming can also be mitigated by combining nightlights with other data types: Zhao et al. (2017) enhanced nightlight intensity values with population data to get a more accurate estimation of spatial economic activity in China. This is based on the observation that there is also an exponential relationship between nightlight intensity and population density. The authors showed that the product of nightlight intensity and gridded population count (called "lit population" by the authors), is a better indicator for economic activity in China than nightlight intensity alone."

Regarding latitude dependencies in nightlight data:

A potential source of latitude dependency in nightlight data are so called stray lights (Lee et al., 2014: "The S-NPP VIIRS Day-Night Band On-Orbit Calibration/Characterization and Current State of SDR Products"). This effect is affecting the high latitudes in both hemispheres. The VIIRS Day-Night Band includes an automated stray light correction (Roman et al., 2018 and Lee et al., 2014). No other relevant latitude dependency issues concerning VIIRS products are known to us. If there were other large scale geographical biases in the data or the relationship between nightlight intensity and asset values, they would be partly mitigated by the fact that the LitPop methodology is applied country by country. This means that gridded $Lit^m Pop^n$ is normalized per country before disaggregation. Thus, inconsistencies between countries are irrelevant.

In order to inform the readers on corrections applied to the nightlight intensity product used here, we add the following sentence in Section 2.2 of the revised manuscript: [p.4, L.105f]

"To isolate luminosity from sustained human activity, the Black Marble nightlight product includes corrections for Lunar artefacts, cloud, terrain, atmospheric, snow, airglow, stray light, and seasonal effects (Carlowicz, 2017; Lee et al., 2014; Román et al., 2018)."

2.4. In line 144 the authors state: 'While the absolute value of LitPop in itself does not bear any interpretable meaning, its relative value in comparison to the national or subnational sum determines how much of a macroeconomic indicator each pixel receives'. Saying that the authors do exactly the opposite in their validation exercise: they use aggregated absolute values from their method to compare it to observed quantities. Even more, this point is very difficult to extract from the manuscript. Only after jumping back and forth in the manuscript I understood that they actually calibrate their method with national GDP data and then compare subnational estimates. This needs to be stated much clearer.

Response: Once again we would like to thank the reviewer to point out an unclear formulation in the manuscript. We agree that the term "interpretable meaning" is misleading here and that further revisions are required to explain the downscaling approach more clearly.

The actual value of $Lit^m Pop^n$ is a unitless digital number per grid cell. A meaningful gridded data set is produced when normalized $Lit^m Pop^n$ is multiplied by a country's total GDP or asset value. As formulated by Zhao et al. (2017): *"Lit population does not correspond to any measurement unit in real life, representing neither people count nor brightness of nighttime lights. It indicates economically weighed-population"*

Changes in the manuscript: In response to the comment, we have refined the text in several places to communicate the following points more clearly, most prominently by providing a revised brief overview of the methodology (Section 2.1), also focusing on the fact that we use total indicator values (i.e. total asset value or GDP) per country and disaggregate them proportional to (normalized) gridded $Lit^m Pop^n$. Revised version: [Section 2.1, p.3, L.85ff]

"2.1 Overview

The core functionality of the LitPop methodology is the spatial disaggregation of national total asset values to obtain a gridded asset exposure product. Gridded nightlight intensity (Section 2.2) and gridded population data (Section 2.3) are combined to compute a digital number at grid cell level (Section 2.5). Physical asset stock values (i.e. produced capital, Section 2.4.1) are then disaggregated proportional to the digital number per grid cell (Section 2.5). This results in the gridded asset exposure dataset presented here. Table 1 provides a detailed overview over the input data.

Instead of the physical asset stock, GDP (Section 2.4.2) or gross regional product (GRP, Section 2.4.3) can be distributed to obtain GDP per grid cell. Because of a lack of subnational produced capital data, GDP and GRP are used to evaluate the methodology by *assessing the subnational disaggregation skill for varied combinations of the input data, as described in Section 2.6."*

Additional explanation added in Section 2.5 of the revised manuscript before Equation 2: [p.6, L.189-192]

"In a second step, gridded $Lit^m Pop^n$ is taken as a relative representation of economic stocks at each grid cell. It is used to linearly disaggregate a total asset values of a country to a geographical grid. More precisely, the value of $Lit^m Pop^n{}_{pix}$ relative to the sum of $Lit^m Pop^n$ over all pixels within the boundaries of the country determines how much of a total value is assigned to each grid cell: […]" (Section 2.5 in Data and Methods)

2.5. The functionality used in Eq. 1 seems rather ad-hoc and only motivated by a study used in China. Have the authors used different approaches, different functional dependencies? What were their findings? Why is the exponential scaling beneficial? Mathematically, only the relative weighting between Lit and Pop is changed by the two exponents. Therefore, the approach could be simplified by using only one exponent that reflects the relative difference between both contributions. Have the authors looked into this direction?

This comment spans different related points and questions regarding the disaggregation methodology presented and evaluated in the paper. We are responding to the more general questions on the selection of the functionality first and treat the specific question concerning the exponents and weighting between *Lit* and *Pop* separately further below.

Ad *"The functionality used in Eq. 1 seems rather ad-hoc and only motivated by a study used in China. Have the authors used different approaches, different functional dependencies? What were their findings?":*

Disaggregating national aggregated socioeconomic indicators proportional to gridded nightlight or population data is a common approach. The decision to work with these two input data types is based (i) on the requirement of a methodology that is based on data that is globally – and freely – available, as well as easily reproducible and updatable; and (2) on the analysis by Zhao et al. (2015, 2017) showing the benefits of combining the two datasets for an admittedly regional study (yet of considerable spatial extent). As explained by Zhao et al. as well as in the Introduction of our manuscript, the combination is mitigating the saturation and blooming artefacts in the nightlight data and exploiting the exponential relationships both between nightlight intensity and economic activity on the one hand, and between nightlight intensity and population density on the other hand. Furthermore, nightlights and population data can be seen as partly complementary representations of asset distribution patterns: Patterns of residential assets correspond well to population while high nightlight intensity correlate well with commercial and industrial assets (i.e. Gunasekera et al., 2015, reference suggested by this reviewer and gratefully acknowledged and integrated into the revised version of the manuscript, c.f. comment 2.14). According to Gunasekera et al. (2015), "infrastructure assets follow a spatial pattern similar to population distribution" (with particular patterns for specific sectors like power production), and literature shows a strong link between "relationship between area of night-time lights and GDP economic activity" and that there is a "correlation of high artificial light intensity at night with urban non-residential areas such as commercial and industrial." Furthermore, risk assessment studies have used higher exponents of nightlight intensity (corresponding to Lit^m) to mitigate the saturation effect (e.g. Aznar-Siguan and Bresch, 2019; Gettelman et al., 2017; Sutton and Costanza, 2002). Based on these previous works, we are confident to combine *Lit* and *Pop* in the applied functional form to disaggregate asset value. The limitations of this approach are discussed in detail in the revised manuscript, for instance in the first three paragraphs of the Discussion (Section 4). The exponents *m* and *n* in Equation 1 can be varied to obtain different multiplicative combinations of the two input data sets (i.e. $Lit^2Pop^1 = Lit * Lit * Pop$ and $Pop^2 = Pop * Pop$). We have used this in the evaluation for a comparison of disaggregation proportional to nightlight intensity or population data alone with combined data, also for different exponents. We have not conducted any comparisons with disaggregation functionalities based on additional data, as we aimed at a globally applicable methodology. The scope of this paper is not to attempt to fit a predictive model (e.g. in the form of $I = a * Lit^b + c * Pop^d$ or other functional forms…) for the countries with GRP data available. The reason being that for a single country, we could fit a function if data is available, but this is not available on a global level and our main requirement for the methodology was global consistency. That's why we decided to provide data based on a global disaggregation proportional to Lit^mPop^n with the same exponents *m* and *n* used for all countries. The evaluation was undertaken to assess the quality and applicability of the disaggregation approach at all and to suggest the most appropriate combination of *m* and *n* based on the data available on a globally consistent basis. Nevertheless, for a specific single country or regional use, any user *might* choose to fit *m* and *n* to any (locally) available data (as the Python code does allow to do so easily).

Changes to the revised manuscript: We have revised the background of the LitPop methodology in the Introduction, better explaining the approach by Zhao et al. (2017) and including more literature making use of non-linearily scaled nightlight data (e.g. Aznar-Siguan and Bresch, 2019; Gettelman et al., 2017; Sutton and Costanza, 2002) and the combination of nightlight intensity with population data for socioeconomic disaggregation (Sutton et al, 2007).

Revision in the Introduction (changes in *blue*): [p.2, L.61-72]

"Brightness can exude from bright pixels to neighboring pixels, causing the brightness in the latter to be overestimated, leading to blooming. This issue occurs especially in large urban areas and on specific surfaces, such as sand and water (Elvidge et al., 2004; Small et al., 2005). As a consequence of saturation, socioeconomic indicators scale rather exponentially than linearly with nightlight intensity (Sutton and Costanza, 2002; Zhao et al., 2015, 2017). To counteract the saturation effect, Gettelman (2017) and Aznar-Siguan and Bresch (2019) used exponentially scaled nightlight intensity as a basis for GDP disaggregation for tropical cyclone risk assessments. ~~These shortcomings~~ Saturation and blooming can also be mitigated by combining nightlights with other data types: Sutton et al. (2007) combined the areal extend of lit area with population data to estimate GDP at a subnational level. Zhao et al. (2017) enhanced nightlight intensity values with population data to get a more accurate estimation of spatial economic activity in China. This is based on the observation that there is also an exponential relationship between nightlight intensity and population density. ~~They~~ The authors showed that ~~"lit population" (LitPop),~~ the product of nightlight intensity and gridded population count (called "lit population" by the authors), is a better ~~indicator~~ proxy for economic activity in China than nightlight intensity alone."

Ad *“Why is the exponential scaling beneficial? Mathematically, only the relative weighting between Lit and Pop is changed by the two exponents. Have the authors looked into this direction?”:*

There is most likely a misunderstanding concerning Equation 1: The exponents m and n do not only weight relatively between *Lit* and *Pop* but they also determine the contrast in the distribution between all grid cells within a country. The larger the exponent, the more value is concentrated on grid cells with large values of *Lit* or *Pop* respectively. For illustration, we have drafted an example with a toy country consisting of 6 toy grid cells:

A) Absolute values

Grid cell ID	*Lit*	*Pop*	*Lit^2*	*Lit^1Pop^1*	*Lit^2Pop^2*	*Lit^2Pop^1*	*Lit^4Pop^2*
1	5	500	25	2500	6E+06	12500	2E+08
2	5	10000	25	50000	3E+09	250000	6E+10
3	50	500	2500	25000	6E+08	1E+06	2E+12
4	50	10000	2500	500000	3E+11	3E+07	6E+14
5	200	500	40000	100000	1E+10	2E+07	4E+14
6	200	10000	40000	2E+06	4E+12	4E+08	2E+17

B) Normalized values

Grid cell ID	*Lit*	*Pop*	*Lit^2*	*Lit^1Pop^1*	*Lit^2Pop^2*	*Lit^2Pop^1*	*Lit^4Pop^2*
1	0.01	0.02	0.00	0.00	0.00	0.00	0.00
2	0.01	0.32	0.00	0.02	0.00	0.00	0.00
3	0.10	0.02	0.03	0.01	0.00	0.00	0.00
4	0.10	0.32	0.03	0.19	0.06	0.06	0.00
5	0.39	0.02	0.47	0.04	0.00	0.04	0.00
6	0.39	0.32	0.47	0.75	0.94	0.90	0.99

The grid cells all have values of Lit of 5, 50, or 200 and values of Pop of 500 or 10000, in permuted combinations. The top table shows the absolute values for varied exponents in *Lit^mPop^n*, the bottom tables shows normalized values for the same data (i.e. each column has the sum 1.0). Please note the differences between *Lit^1Pop^1 and Lit^2Pop^2 and* between *Lit^2Pop^1 and Lit^4Pop^2* respectively: The larger the exponents, the more *normalized* value is concentrated at grid cell 6 with the largest values of *Lit* and *Pop*. Thus, the approach could not be reproduced using only one exponent as suggested by the reviewer.

For clarification, we included the following sentences into the revised script at the end of Section 2.5: [p.6, L.198-200]
“The exponents m and n do not only weight relatively between Lit and Pop but they also determine the contrast in the distribution between all grid cells within a country. The larger the exponent, the more value is concentrated on grid cells with large values of Lit or Pop respectively.”

2.6. The authors say they use two skill scores in line 178. Later they widen their analysis to three skill scores (e.g. Fig 3), which they interchangeably call methods as well. The authors should adjust their manuscript accordingly and stick to one naming convention.

Response: In order to improve the readability, we have revised the wording in the Methods and the Results sections: We now consistently refer to three "*skill metrics*", namely ρ, β, and RMSF and do not refer to them as "scores" or "methods" anymore. [first mentioning at p.7, L.223]

2.7. The relevance of skill score 'beta' remains obscure (line 185). First, it is fully unclear about what slope the authors are talking. Second, the concept of linear regression in this context is fully unclear. Third, skill score 'beta' basically contains the same information as 'rho' (eq. 4), it is just a different scaling with respect to the standard deviations. I therefore do not understand why beta is needed in the first place and would ask the authors to remove one of them (beta or rho) as they are based on the same information.

Response: In the evaluation, we are using the Pearson correlation coefficient ρ and the slope of linear regression β as complementary skill metrics. The metrics are computed from modelled (i.e. disaggregated) vs. reference (i.e. reported) normalized gross regional product (nGRP) per subnational unit (region, district, etc.) within each country. The confusion around the linear regression used in the evaluation is well taken. We agree that ρ and β are not completely independent metrics.

Still, the metrics ρ and β do indeed convey complementary information on the disaggregation skill of the applied combinations of exponents in the disaggregation function: ρ tells us to which degree modelled and reported nGRP correlate, i.e. if there is a strong linear relationship between the two variables. However, there could be a perfect correlation (ρ=1) with a very steep or very flat slope β. For this reason, ρ is sometimes referred to as a measure of "potential skill". The slope β tells us, whether there is a systematic over- or underestimation of economically large regions in the disaggregated data. For β>1, economically large regions are overestimated (as we found for Pop^2), for β<1, economically large regions are underestimated by the disaggregation (as we found for Lit^1). However, β alone does not convey any information on the correlation between the two variables, i.e. there could be a perfect slope (β=1) for variables with a very weak linear relationship.

In more mathematical terms: β is calculated by scaling ratio of the stanrd deviations of the two variables with ρ ($\beta = \rho \cdot \sigma_{mod}/\sigma_{ref}$). While σ_{ref} is constant for each country, σ_{mod} changes with changing exponents *m* and *n*. Thus, β is indeed not just a scaled version of ρ. Instead, it carries additional information as discussed above. We could also use ρ and $\sigma_{mod}/\sigma_{ref}$ instead of ρ and β to assess the disaggregation skill. The reason we use β is that by scaling the standard deviations with ρ, the slope has a more straight-forward meaning related to the aim to select a combination of m and n that produces the best linear relationship between modelled and reference nGRP. Based on our arguments presented above, we propose to keep considering both metrics for evaluation.

For clarification, we include parts of above reasoning in Section 2.6 of the revised manuscript (changes in *blue*): [p.8, L.235-243]

“The correlation coefficient ρ is a widely used ~~score~~ metric and straight forward to interpret and communicate: A value of 1 ~~means~~ indicates a perfect positive linear correlation between the two variables while a value of 0 ~~means~~ indicates that there is no linear correlation. However, ρ is no direct measure of the deviations of $nGRP_{mod}$ from $nGRP_{ref}$ and yields no information regarding the slope of the linear relationship. Therefore, it only represents a potential skill and needs to be evaluated in combination with a measure of the slope. The slope of the linear regression conveys the information, whether there is a systematic over- or underestimation of economically large regions in the disaggregated data. Therefore, $\beta = \rho \cdot \sigma_{mod} / \sigma_{ref}$ is calculated to complement the analysis: β larger (lower) than 1 implies an overestimation (underestimation) of the GRP of ~~economically strong~~ regions with relatively large GRP and an underestimation (overestimation) of ~~economically small~~ regions with relatively low GRP in the downscaling. Together, ρ and β allow for an evaluation of the linear fit between modelled and reference data.“

2.8. The range of exponents m and n explored in the validation seems random and bares any motivation. What is the motivation for the range of exponents explored? I strongly encourage the authors to motivate their validation and to conduct a more stringent validation accordingly.

Response: Please refer to the response to comment asked in comment 1.10: *“Why did authors choose to vary Lit more than Pop?”*

In Section 3.2 of the revised manuscript, we add the following clarifying statement: [p.9, L.277f]

“These exponent combinations were selected based on examples in the literature and then explored iteratively, stopping at combinations with decreased skill compared to lower order combinations.”

2.9. The validation section (3.2) needs to clarified and amended. On first read (see my point raised before) I had the understanding that the analysis around Fig. 3 is based on 14 data points only (E.g. the caption of Fig. 3 points at this as well). Only later I understood that the authors use many data points (14 x subnational regions). The number of data points is never mentioned, however. How is the interquartile range defined? Please be much more precise and proactive.

Response: We would like to thank both reviewers for their various comments regarding the validation section in the manuscript. Based on this and other comments, we have thoroughly revised both sections on that topic (both in the Data and Methods and in the Results). Most prominently, we have replaced the term “validation” with “evaluation” (c.f. response to comment 1.0).

In response to the particular misunderstanding brought up here regarding the exact methodology applied for the evaluation and the number of data points used, we revised the text both in Section 3.2 and 2.6 (formerly 2.7), as well as in the newly introduces data overview in Table 1. The aim of the revision is to point out more clearly now that the evaluation is based on 507 data points, corresponding to normalized reported and modelled GRP data for a total of 507 sub-national regions in 14 countries.

We added the following clarifying statement in Section 2.6 in Data and Methods: [p.7, L.217-220]

"The LitPop approach's skill in disaggregating asset exposure cannot be assessed directly due to the lack of reference asset value data on a subnational level. Therefore, GDP and GRP are used instead for an indirect evaluation of the methodology. GDP and GRP are used to assess the subnational disaggregation skill, comparing varying combinations of the exponents m and n in $Lit^m Pop^n$."

In Section 3.2 (Results) of the revised manuscript, we replaced the opening paragraph as follows: [p.9, L.273-280]

Old: *"The downscaling within countries is validated by comparing the downscaled and reported subnational GDP with three 225 quantitative methods. The Pearson correlation coefficient ρ, linear slope parameter β, and root-mean-squared fraction RMSF per country are shown in Tables A2. To compare the overall performance of the different methods, median and spread of the scores are compared in Figure 3 and Table A3."*

Revised: *"To evaluate the performance of the LitPop methodology, we compute and compare the disaggregation skill in regards to GDP for varying exponents m and n in $Lit^m Pop^n$ (Eq. 1 and 2). Here, we show the comparison based on 14 countries with a total of 507 regional GRP data points available. The 14 countries make up 67% (USD 168 trillion) of the total dataset's exposure and 64.5% (USD 52 trillion) of global GDP in 2014. Ten combinations of m and n are assessed: Lit^1Pop^1, Lit^1, Lit^2, Lit^3, Lit^4, Lit^5, Pop^1, Pop^2, Lit^2Pop^1, and Lit^3Pop^1. These exponent combinations were selected based on examples in the literature and then explored iteratively, stopping at combinations with decreased skill compared to lower order combinations. For each country and exponent combination, the median and the spread of three skill metrics are compared: ρ, β, and RMSF (Fig. 3 and Tables A2 and A3)."*

2.10. Based on the redundancy of either beta or rho (stated above) and your diverging findings for different skill scores within your validation, I find the final decision to use the downscaling with m=n=1 (line 240) very ill-founded. At this stage I would expect a more thorough and stringent assessment of the different exponents and functionalities(see comment above). Otherwise, the full validation exercise seems redundant.

Response: This point is well taken. The comment connects different comments by both reviewers related to the Sections on validation/evaluation. Indeed, we are not validating but comparing different exponents in the evaluation exercise. Please refer to our response to comment 1.0 by the first reviewer for a broader discussion of the limitations of the evaluation and on the resulting changes regarding the reframing of the comparison as evaluation instead of validation.

Regarding the specific concerns raised by this comment: The aim of the manuscript is to present a global asset exposure data set, document the underlying data and methodology (the so called LitPop methodology), and evaluate the methodology by comparing different variations of the downscaling function and selecting the most appropriate combination of exponents for the production of the globally consistent version of the asset exposure data. We understand that this can seem redundant with regards to the structure of the manuscript. In our actual work flow however, the evaluation was undertaken before the global data set was produced to be able to decide on the actual combination of m and n to use. We understand the concerns related to the evaluation that arise from the finding that **(1)** no other functionalities besides Lit^mPop^n were assessed, **(2)** only a limited set of possible values for the exponent combinations for m and n were compared, and **(3)** m=n=1 does only perform best for the skill metrics ρ and β, but not for RMSF. We also agree that based on the quantitative evaluation, we could have also argued for another choice. We argue that given the global availability of both nightlight intensity and population data and the positive effect of including population data with regards to saturation and blooming, the chosen functional form and exponents are an appropriate choice with regards to the purpose of the data set and the methodology.

For this we argue by responding to each of the three points of criticism formulated in the reviewer's comment and a summarizing statement:

Ad (1): The functional form Lit^mPop^n was selected based on previous studies disaggregating asset exposure value or GDP proportionally to either gridded population data (here: Pop^1), higher exponents of (here: Lit^m with m>1) or on the product of both data types (i.e. Lit^1Pop^1). Please refer to our response to comment 5 by the same reviewer for more details. The aim of the whole exercise presented in our manuscript was to apply these well-tried approaches within a globally consistent methodology and evaluate varied combinations of *Lit* and *Pop* in accordance with previous applications. While the comparison with different functional forms for combining the two input data types would be beneficial, such a meta study would go beyond the scope of this study.

Ad (2): The range of exponents considered for evaluation was determined based on literature and an iterative approach. Please refer to the responses to the question asked in comment 1.10 by Anonymous Reviewer 1: *"Why did authors choose to vary Lit more than Pop?"* for more details.

Ad (3): Regarding the partial redundancy of ρ and β, please refer to the response to comment 7. As we will state more clearly in the revised manuscript (see changes below). Regarding the deviating results between ρ and β on the one hand and RMSF on the other hand: We chose to consider all three skill-metrics because they convey complementary information. ρ and β are computed based on covariance and standard deviation which are representing the distribution of the total values of the input variables (here: nGRP). While they are relatively susceptible to outliers (i.e. putting larger weight on larger values), they represent the distribution of total values. RMSF, on the other hand, weights the relative deviation between modelled and reference nGRP equally, independently of its total value. Prioritizing a better distribution of total values over relative performance, we conclude that Lit^1Pop^1 can be considered the most adequate combination of *Lit* and *Pop* for the subnational downscaling of GDP. Still, we decided to include RMSF in the evaluation sections in order to be transparent regarding the fact that there is no combination of exponents available that performs best with regards to all skill metrics.

For a clearer statement of the results of the evaluation, we added the following in Section 3.2. of the revised manuscript: [p.10, L.293-300]

"Within the set of combinations exclusively based on Lit (n=0), the skill metrics β and RMSF perform best for Lit^4 (Fig. 3b,c), with median ρ improving for larger values of m, however changing little from Lit^4 to Lit^5 (Fig. 3a).

Based on the comparison of the disaggregation skill with varying exponent m and n, there are two candidates for the most adequate functionality: Lit^1Pop^1 (best ρ and β) and Lit^4

(best RMSF and best performance for n=0). The skill metrics of linear regression, ρ and β, give a better representation of the disaggregation skill for the absolute values than RMSF which is based on the relative deviation per data point. Prioritizing a better distribution of total values over relative performance, we conclude that Lit^1Pop^1 can be considered the most adequate combination of Lit and Pop for the subnational downscaling of GDP. For countries with a lack of highly resolved population data, alternative data sets could be produced based on Lit^4 alone."

2.11. Line 187 (and others in the following): the notion of economically strong (or large)and weak regions is not very well defined. The reader can sort of understand what the authors hint at but it remains very unclear. How do they distinguish strong from weak regions? What is the precise criterion? Does this hold nationally or internationally?

Response: We would like to thank the anonymous reviewer for pointing out that ambiguity. With economically strong/weak regions, we referred to the GRP of the region relative to the other regions in the same country. The differentiation between regions thus holds only nationally. This is the relevant scope for evaluation, as the skill metrics are computed separately for each country.

For clarification, we changed the wording in Section 2.6 (formerly Section 2.7) to:

"regions with relatively large/low GRP"

Particular change (new in *blue*): [p.8, L.241f]

"β larger (lower) than 1 implies an overestimation (underestimation) of the GRP of ~~economically strong~~ regions with relatively large GRP and an underestimation (overestimation) of ~~economically small~~ regions with relatively low GRP by ~~in~~ the downscaling within one country."

In Section 3.4 (formerly 3.3) regarding the example in Mexico, we changed the wording accordingly, now referring to *"districts with relatively low GRP"* instead of *"smaller districts"*. [p.12, L.325]

2.12. The sentence 'There is probably a lot of housing and infrastructure in suburban México that is used by a population that works in the city and thus contributes to the GRP of Mexico City' (strange comparison of stocks and flows) and the following discussion is very difficult to digest for the non-expert reader. I find this discussion very relevant and think it should be extended here or at some other point in the manuscript as it directly links to many relevant issues: a) What does nightlight intensity actually capture? Assets or GDP? b) What is the highest downscaling resolution one should aim at when population is most likely a better proxy of the location of assets but night-light also captures economic activity (e.g. driving cars)? Also in the light of above sentence when GDP and assets seem to be separated by municipal boundaries. c) how can the interaction of both data sources most efficiently be combined? How does the present methodology add to this discussion? How can the different exponents be interpreted in this respect?

The questions raised by the reviewer are indeed very valid and worth to research in greater detail. We agree that the discussion we have offered in the manuscript so far is a stub and would require further explorations. However, a detailed analysis of the case study would be beyond the scope of the paper. The aim of the paper is not to research into questions like these on that level. As a consequence, we changed the structure of the whole Results section (putting more focus on the main results, i.e. the data set) and propose to remove the rudimentary interpretation in the Results section on Mexico (formerly Section 3.3), including the sentence quoted by the reviewer. Still, we keep a revised version of the Section at the end of the revised Results section. The reason is that the purpose of showing the example of Mexico is to illustrates the limitations of the disaggregation approach and gives some insight into the data behind the evaluation. The revised Section 3.4, as pasted below, presents and discusses the nGRP data closer to what is in the data and refrains from unsupported interpretations: [Section 3.4, p.12, L.321-335]

"The skill metrics for the subnational disaggregation of GDP in the country Mexico shows low value of ρ compared to most other countries for all tested values of m and n (ρ=0.76 for Lit^1Pop^1, c.f. Table A2a). The example of Mexico is presented here to illustrate limitations and uncertainties of the disaggregation approach. Figure 5 shows the data behind the evaluation for Mexico, i.e. modelled and reference nGRP for all 32 districts of Mexico. The corresponding plot data can be found in Table S2 as supplementary material. While the LitPop methodology performs well for most of the districts with relatively low GRP, it fails to reproduce reference nGRP for the main (capital) metropolitan region consisting of the districts México and Mexico City (Distrito Federal).

The two districts with the largest GRP of the highly centralized country are Distrito Federal (Mexico City district) with a reference nGRP of 17.4% and México district (8.7%), surrounding the Distrito Federal. Asset exposure maps of the metropolitan region are shown in Figure A1 in the Appendix. The disaggregation of GDP underestimates nGRP for Mexico City district while overestimating the value for México for all evaluated combinations of m and n (nGRP for Lit^1Pop^1, Lit^3, and Pop^1 are shown in Figure 5). The overestimation of México district's nGRP indicates that the district has an over-proportional nightlight intensity and population count compared to a relatively low reference nGRP. Both districts combined sum up to modelled nGRP values of 11.2 to 17,6% for Lit^m, 20.8% for Pop^1, and 26.5% for Lit^1Pop^1 (Table S2), the latter agreeing well to a combined reference nGRP of 26.1%."

Additionally, we are taking these results up in the Discussion (Section 4), by adding the following paragraph to the revised manuscript: [p.14, L.382-384]

"The example of Mexico (Section 3.4) illustrates the limitations of the LitPop methodology when it comes to the disaggregation of GDP within a metropolitan area: While the disaggregation of GDP proportional to Lit^1Pop^1 nicely reproduces the summed nGRP of the metropolitan area, methodology fails to reproduce the distribution of nGRP between the two districts making up the metropolitan area."

2.13. The discussion in line 284-292 is very vague as it is very hard to judge for the reader when to apply the authors' recommendation: high-resolution vs. coarsely resolved?, use a higher exponent of nightlights instead...instead to what? Why use exponent n=3 when this was never a potentially recommended value in the validation before? The discussion on auxiliary data should be placed somewhere else.

Response: In the lines the reviewer is referring to, we recommended an exponent for Lit >= 3 for countries with coarsely resolved population data available (as the level of detail in the GPW population data varies between countries). Calling the exponent n instead of m (for

Lit^m) was a typographical error and we would like apologize for that mistake that might have added to the confusion. The recommendation is based on the evaluation result that *Lit^3*, *Lit^4* and *Lit^5* show larger disaggregation skill than *Lit^1*. This is now better documented in the Results Section of the revised paper (c.f. changes to the text in the Results as applied in response to the same reviewer's comment 10). Based on the results and the reviewer's comment on the vagueness of the recommendation, we have revised the lines in the Discussion with a focus on precision, please find the revisions below: [p.14, L.364f]

Old: *"For countries without a high-resolution distribution of population in the gridded dataset, an exposure map based on $Lit^m Pop$ (is equivalent to one based on Lit^m alone. For more locally refined risk assessments, in countries with coarsely resolved population information, we advise to use a higher exponent of nightlights instead, i.e. $n \geq 3$."*

Revised: *"For countries without a high detail level in the population data available, asset exposure based on $Lit^m Pop^n$ is more or less equivalent to one based on Lit^m alone. For regional application in these countries, evaluation results suggest that disaggregation proportional to Lit^4 could distribute asset values best in the absence of detailed population data."*

Ad *"The discussion on auxiliary data should be placed somewhere else.":* we moved the discussion on auxiliary data into the paragraph on "scalability and flexibility". It is also reformulated and expanded, as can be seen in our response to comment 2.14 below.

2.14. It is very unfortunate that the validation was (or could) only be conducted for 14 countries and no low-income country. The subsequent application of this method to all countries globally has to be treated with caution. In the present manuscript I am missing a detailed discussion of the reliability of the dataset for specific regions and/or income groups and a discussion of potential workarounds. What is the result of the authors' validation in terms of income groups? Is there any information (e.g. trends with income) that could be valuable for low income countries not treated here? What about very small countries, islands, etc? How could other data sources (e.g. household survey data from the Worldbank) be used to improve the data? What has been conducted with this respect in the literature so far (c.f. following paper and the references cited there: Gunasekera, R., et al. (2015). "Developing an adaptive global exposure model to support the generation of country disaster risk profiles." Earth-Science Reviews 150:594-608.)?

Response: The limitation of the evaluation to 14 countries from the income groups 2-4 was brought up by both reviewers. While these limitations were already communicated in the original manuscript, we agree that the communication and discussion should be expended and cautioning remarks added. Please also refer to our response and revisions in reply to the first reviewers comments 1.0 and 1.15.

As this comment is very dense and raises various relevant issues, some beyond the scope of the present paper, indeed. Please find our direct response to the specific points raised below:

Ad *"The subsequent application of this method to all countries globally has to be treated with caution. In the present manuscript I am missing a detailed discussion of the reliability* *of the dataset for specific regions and/or income groups and a discussion of potential workarounds.":*

We have revised the second paragraph in the Discussions in order to expand the discussion of the limited scope of the evaluation and its consequences, including possible workarounds (changes in *blue*): [p. 13f, L.342-367]

"Based on globally available input data, the LitPop methodology ~~performs well~~ can be applied across countries from different continents and income groups without any customization. While the presented data set is not complete, it provides data for 224 countries contributing 99.9% of global GDP. Therefore, LitPop-based asset exposure data can be used as a basis for globally comparable economic risk assessments. However, the evaluation of the disaggregation skill of the approach presented here is limited to 14 OECD countries. It should be noted that due to lack of data we were not able to evaluate the method's performance for low income countries (World Bank income group 1). Therefore, the application of the asset exposure data for local assessments in countries within low income groups should be treated with caution. Another caveat to global consistency is the fact that the quality and resolution of the underlying population dataset varies between countries, as discussed in greater detail in the next paragraph. As a consequence of these limitations, asset exposure data should be validated against local data before application for local risk assessments, especially in low income countries."

Ad *"What is the result of the authors' validation in terms of income groups? Is there any information (e.g. trends with income) that could be valuable for low income countries not treated here? What about very small countries, islands, etc?":*

While this would definitely be a valuable contribution for future studies conducting asset value downscaling, a more detailed analysis of a potential income-group dependency of downscaling functionalities would be beyond the scope of this publication. A comparison of skill metrics between the 14 countries did not show a clear picture in term of differences between income groups.

We thus added the following as an outlook to the Conclusion section (additions in *blue*): [p.15, L.420-424]

"Future research and development could focus on the integration of higher resolved population data and other ancillary data sources as they become available globally~~, and validation of the disaggregated asset exposure values against empirical data~~. Validation against subnational asset value and empirical asset stock inventories yields the potential to evaluate and further improve the accuracy of asset exposure downscaling, both for global and regional applications. Regional validation could inform the choice of the most appropriate downscaling functionality for different income groups and world regions."

Ad *"How could other data sources (e.g. household survey data from the Worldbank) be used to improve the data? What has been conducted with this respect in the literature so far (c.f. following paper and the references cited there: Gunasekera, R., et al. (2015). "Developing an adaptive global exposure model to support the generation of country disaster risk profiles." Earth-Science Reviews 150:594-608.)?":*

We would like to thank the reviewer for bringing the key publication by Gunasekera, R., et al. (2015) to our attention.

The exposure data model presented by Gunasekera et al. (2015) overlays different methodologies to represent a gridded asset exposure inventory of a country as comprehensively as possible. Their methodologies include exposure disaggregation, building typology and vulnerability distribution, and asset value determination. Among other data sources, their model includes the disaggregation of GDP proportional to gridded population data as well as national asset value estimates that are downscaled. Unfortunately, the resulting dataset is – in contrast to our method and all results – not available online. With the LitPop methodology, we provide a simplified approach for exposure disaggregation only, excluding building typology and vulnerability distribution. We find that the approaches used by Gunasekera et al. (2015) and also other studies referenced in our manuscript (e.g. De Bono and Mora, 2014, and Murakami and Yamagata, 2019) support the basic approach of the LitPop methodology while showing how the approach could be refined by combination with other data sources. The LitPop methodology and the provided open-source python module have a lower threshold for reproduction and updates when updated nightlight or population data becomes available. However, the LitPop methodology provides less precision when it comes to the assets of specific sectors and building typology.

In summary, we happily include reference to Gunasekera, R., et al. (2015) in the revised manuscript and briefly discuss the LitPop methodology in with respect to their approach.

Revised first references in the Introduction: [p.1, L.33-50]

"Due to the lack of comprehensive asset stock inventories, large scale asset exposure maps are often estimated top-down, using downscaling techniques (De Bono and Mora, 2014; Gunasekera et al., 2015; Murakami and Yamagata, 2019)

[…]

An alternative methodology to model global asset exposure based on the combination of diverse data sets was presented by Gunasekera et al. (2015). The authors combined data on built-up area, building typologies, and construction cost with sector specific asset data and GDP disaggregated proportional to population density. Unfortunately, the source code and resulting exposure data have not been made publicly available. Reproducing these previously mentioned exposure modelling efforts is beyond the scope of most economic disaster risk assessments and climate change adaptation studies."

Amendments in the Discussion: [p.14, L.389-394]

"Additionally, the asset exposure data could be further refined by including auxiliary data, such as road networks and land cover (Geiger et al., 2017; Murakami and Yamagata, 2019), or mobile phone cell antenna density (Brönnimann and Wintzer, 2018). In order to include sector specific assets not represented by the LitPop methodology, i.e. power plants or mines in unpopulated areas, additional sector specific asset inventories should be included (Gunasekera et al., 2015). For a globally consistent approach, sectoral data should however be included with caution, as such datasets are prone to regional or national biases."

2.15. The concept of intermediate downscaling appears in line 257 very ad-hoc and is used thereafter without further explanation.

Response: By "intermediate downscaling" we refer to the idea of disaggregating total asset value to subnational administrative units proportional to their GRP before disaggregation to grid level. This approach could potentially mitigate geographical biases within countries with large internal structural differences. We initially mentioned this approach here because the functionality is implemented in the LitPop-module of the CLIMADA repository (https://github.com/CLIMADA-project/climada_python/blob/master/climada/entity/exposures/litpop.py). However, we agree with the reviewer that the mentioning in the manuscript is confusing. Since intermediate downscaling is not used for the data set presented, the mentioning is not required.

Changes: We therefore removed both appearances/discussions of the term in the revised manuscript.

2.16. LitPop as a top-down approach is first introduced in line 302. It would make much more sense to make this statement much earlier otherwise one should avoid this notion in general.

Response: We initially introduced the term "top-down" in the discussion to mark the difference to more local (bottom-up) or sector specific approaches to create asset exposure data, i.e. with mapping on the ground or the integration of industry data bases. We agree with the reviewer that this late introduction of the term leads to more confusion than clarification and is not needed to communicate the intended differentiation. Thus, we replaced the term "top-down approach" in the revisions, mainly by the better introduced concept of "disaggregation". We aligned the terminology throughout the manuscript to improve readability, using the term disaggregation more consistently.

In the particular paragraph in the Discussion (Section 4) the reviewer is referring to, we revised the text accordingly and remove the unnecessary remark on the "top-down" nature of the approach (changes in *blue*): [p.14, L.376ff]

"Since the CLIMADA repository is open-source, the LitPop methodology can ~~easily~~ be amended to include alternative data sources and versions of both gridded nightlight, population, ~~asset base~~ and total asset values or other socioeconomic indicators to expand and update the ~~repertory of the top down exposure data model~~ asset exposure data. The LitPop methodology was developed to provide ~~a~~ globally consistent asset exposure ~~base data~~ for ~~large~~global-scale ~~disaster~~ physical risk modelling. While it could be used for other applications as well, the limitations of its scope should be noted: ~~The top down disaggregation approach implemented here~~ The LitPop methodology does not account for differences in infrastructure types and vulnerability. In addition, gridded data may cause poor scoping of areas most vulnerable ~~to risk~~, or those with more exposed population. […] ~~Thus, the applicability~~ The use for local ~~based~~ or sector specific applications ~~and detailed socio-economic risk assessments~~ is limited ~~by the top down nature of our methodology~~ without the addition of sector specific data sets."

2.17. The term 'exposure' is used differently throughout the manuscript. It seems that he authors use it for 'asset exposure' but this is not fully clear. Exposure is very general and could be understood as population or GDP exposure as well. Therefore, I encourage the authors to be more precise and use the expression 'asset exposure' every time they mean it.

Response: We have amended the text as proposed by the reviewer, adding the term *"asset"* for clarification in front of many different appearances of *"exposure"* (most prominently in the **title** of the manuscript: *"Asset exposure data for global physical risk assessment"*)

The single changes in the text are not listed here, as they are spread through the whole manuscript.

2.18. All abbreviations (e.g. GDP, GRP), all variables, and all subscripts (e.g. pix) need to be explained at first use, even if the authors think that they are self-explanatory. Thereafter another redefinition should be avoided and the authors should stick to their abbreviations.

Response: We have revised the first appearances of following abbreviations, variables, and subscripts based on the reviewer's comment: *GDP, GRP, IQR,* ρ, β, *RMSF, pix*.

The single changes in the text are not listed here, as they are spread through the whole manuscript.

2.19. Figure 4: The usage of Mexico (country) and México (region) is very confusing fort he reader. Clearly state this difference and maybe use 'México region' to underline the difference.

Response: We would like to thank the reviewer for pointing out the confusion caused by the district names in Mexico. We would suggest to adapt the reviewer's suggestions to use the term "México district" instead of "México region" or just "México". All mentions of México (also in Figure 4) were adapted accordingly in the revised manuscript.

Revisions in Section 3.4 of the revised manuscript (changes marked in *blue*): [p.12, L.321ff]

"~~In the validation in Section 3.2,~~ The skill metrics for the subnational disaggregation of GDP in the country Mexico shows low ~~correlation~~ values of ρ *compared to most other countries for all tested values of m and n (*ρ*=0.76 for* Lit^1Pop^1*, c.f. Table A2a). […] Figure ~~5~~ 4 shows the data behind the evaluation for Mexico, i.e. modelled and reference nGRP for all 32 districts of Mexico. The corresponding plot data can be found in Table ~~S.1~~ S2 as supplementary material. While the LitPop methodology works well for most of the ~~smaller~~ districts with relatively low GRP, it fails to reproduce the nGRP for the main (capital) metropolitan region consisting of the districts México and Mexico City (Distrito Federal)."*

Further down in the text we consistently replace *"México"* with *"México district".* [p.13, L.329, 332]

Minor points:

2.20. The discussion in line 31 should include another freely available gridded GDP dataset: Kummu, M., et al. (2018). "Gridded global datasets for Gross Domestic Product and Human Development Index over 1990-2015." Sci Data 5: 180004.

Response: The reference was added as suggested by the reviewer. The cumulated changes to the paragraph are shown below in the response to comment 2.22.

2.21. The reference Murakami et al is outdated. Please update to: Murakami, D. and Y. Yamagata (2019). "Estimation of Gridded Population and GDP Scenarios with Spatially Explicit Statistical Downscaling." Sustainability 11(7).

Response: The reference was updated accordingly.

2.22. Line 34: The statement on high-resolution GDP data availability for academic purposes only is not true. Upon checking the reference I found that the data is freely available. The corresponding reference should be included in the manuscript: Geiger, Tobias; Daisuke, Murakami; Frieler, Katja; Yamagata, Yoshiki (2017): Spatially-explicit Gross Cell Product (GCP) time series: past observations (1850-2000) harmonized with future projections according to the Shared Socioeconomic Pathways (2010-2100).GFZ Data Services. http://doi.org/10.5880/pik.2017.007

Response: Thank you for pointing out that the data has been made publicly available. We were not aware of the publication of the GCP dataset under a creative commons (CC) 4.0 license when we first submitted the manuscript. Based on the reviewer's comments 2.20 to 2.22, we have updated the reference and the statement on availability as follows (revised version of manuscript text shown in *blue*): [p.1f, L.37-41]

Old (Lines 34-37): *"Assuming that human presence and activity are proxies of economic output, downscaling of gross domestic product (GDP) has been based on population combined with land-use, road networks, and locations of airports (Murakami and Yamagata, 2016). While high resolution yearly GDP maps based on this approach were created for academic use (Frieler et al., 2017), there is no recent global high-resolution exposure dataset available for unrestricted use known to us.*

Revised: *"Assuming that human presence and activity are proxies of economic output, downscaling of GDP has been based on geographical population data (Kummu et al., 2018) and on population combined with land-use, road networks, and locations of airports (Murakami and Yamagata, 2019). High resolution yearly GDP maps based on these approaches are publicly available (Geiger et al., 2017; Kummu et al., 2018)."*

2.23. Line 55 (and others): the reference to Zhao et al. cannot be found in the list of references.

Response: We would like to thank the referee for pointing out the error in this crucial reference. The reference was mistakenly listed under "Naizhuo Zhao" instead of "Zhao, N.". We have corrected this mistake in the revised manuscript.

2.24. Line 177: What does the exponent '5' stand for in nGRP_i? Looks like a footnote which I am unable to locate. Same issue in line 189 and 228.

Response: These superscript numbers are indeed remnants of footnotes that existed in an earlier draft. We would like to apologize for the confusion. The superscript numbers are removed in the revised manuscript. [p.7]

2.25. Line 182: Seems like the separated equation for rho got lost and appears inline now. The enumeration eq. 4 is also missing.

Response: Equation numbers and references were revised according to the reviewer's observation. The equation for rho is eq. 4 and was labelled accordingly. [p.8, L.234]

2.26. Figure 2: I do not understand what do you mean by log-normal colorbar? I would appreciate the colorbar to have a label. What kind of USD do you use here? PPP-adjusted, current or real? This applies similarly for Fig A1.

Response: The description of the colorbar as "log-normal" was indeed incorrect. The colorbar shows disaggregated asset values in current USD of 2014 on a logarithmic scale. This information was added to the caption in the revised manuscript. We have added a label to the colorbar of the figures, as suggested by the reviewer. Additionally, we have added the information that it is current USD to the captions of Figures 2 and A1. Revised caption: [p.12, top]

"Figure 4: Maps of disaggregated asset exposure value. Values are spatially distributed proportional to nightlight intensity of 2016 (Lit^1, a), population count as of 2015 (Pop^1, b), and the product of both (Lit^1Pop^1, c) for metropolitan areas in the United Kingdom (GBR) and India (IND). The maps are restricted to the wider metropolitan areas of London (0.6°W-0.4°E; 51-52°N) and Mumbai (72-73.35°E; 18.8-19.4°N) respectively. The colorbar shows asset exposure values in current USD of 2014 per pixel of approximately 1 km^2."

2.27. Line 219: replace top -> bottom

Response: The word was replaced as suggested. [p.12, L.317]

2.28. Line 326-328: The information on RMSF is repeating what the authors mentioned earlier around line 190.

Response: This comment is most likely referring to Line 236-238 (not 326-328). To remove the redundancy, the information on RMSF were removed in the Results section. The following sentence was moved to the Methods Section where RMSF is first introduced, since it is not redundant with the information provided already: [p.8, L.247f]

"A RMSF-value of 2 means that on average, the modelled GRP deviates by a multiplicative factor of 2 from the reference value."

2.29. Line 240: remove 'an'

Response: The 'an' was removed. [revised paragraph: p.10, L.295-300]

2.30. Line 243: A reference to the data in the appendix would be very helpful here as the reader is unable to extract the information for Mexico from section 3.2.

Response: The paragraph was rewritten for more clarity. As part of this, we added a reference to Table A2a in the Appendix. Lines 242-247 were replaced by the following, as shown in response to comments 2.12. and 2.19 in greater detail: [p.12, L.321ff]

"The skill metrics for the subnational disaggregation of GDP in the country Mexico shows low values of ρ compared to most other countries for all tested values of m and n (ρ=0.76

for Lit[1]Pop[1], c.f. Table A2a). […] Figure 5 shows the data behind the evaluation for Mexico, i.e. modelled and reference nGRP for all 32 districts of Mexico. The corresponding plot data can be found in Table S2 as supplementary material. […] Asset exposure maps of the metropolitan region are shown in Figure A1 in the Appendix."

2.31. Line 264: the reference for Pittore et al cannot be found in the list of references.

Response: Again, we would like to thank the referee for pointing out the error in this crucial reference. The reference was mistakenly listed under "Massimiliano Pittore" instead of "Pittore, M.". We have corrected this mistake in the citation catalogue for the revised manuscript.

2.32. Line 334: replace get > become

Response: The word was replaced as suggested. [p.15, L.421]

2.33. Caption figure A1: replace 'the Mexico and USA' > 'Mexico and the USA'

Response: The figure caption was revised in accordance to changes to the caption of Figure 4 [p.12; p.19]

References:

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~~Exposure~~Asset exposure data for global physical risk assessment

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Abstract. One of the challenges in ~~the~~ globally consistent ~~assessment~~assessments of physical climate risks is the fact that asset exposure data are either unavailable or restricted to single countries or regions. ~~Here, we~~We introduce a global high-resolution asset exposure dataset responding to this challenge. The data are produced using "lit population" (LitPop), a globally consistent methodology to ~~estimate spatially explicit exposure~~ disaggregate asset value data proportional to a combination of nightlight intensity and geographical population data. By ~~multiplying~~combining nightlight and population data, unwanted artefacts such as blooming, saturation, and lack of ~~resolution~~detail are mitigated. Thus, the combination of both data types improves the spatial distribution of macroeconomic indicators. ~~To evaluate~~Due to the ~~predictive skill~~ lack of reported subnational asset data, the ~~downscaling approach,~~disaggregation methodology cannot be validated for asset values. Therefore, we compare disaggregated GDP ~~distributed proportional to LitPop to~~ per subnational administrative ~~regions is compared~~region to ~~reference~~reported gross regional product (GRP) values for evaluation. The ~~results~~comparison for 14 industrialized and new-industrialized countries ~~show~~shows that the ~~predictive~~disaggregation skill ~~of LitPop is higher than~~for GDP using nightlights or population data alone~~.~~ is not as high as using a combination of both data types. The advantages of ~~this approach are: high predictive skill,~~LitPop are: global consistency, scalability, openness, replicability, and low entry threshold. The ~~flexibility of the~~ open-source LitPop methodology and the publicly available asset exposure data ~~and methodology offers~~offer value for manifold use cases ~~for~~, including globally consistent economic disaster risk assessments and climate change adaptation studies, especially for larger regions yet at considerably high resolution. Code is published on GitHub as part of the open-source software CLIMADA (CLIMate ADAptation) and archived in the ETH Data Archive with link: http://doi.org/10.5905/ethz-1007-226 ~~(Bresch et al., 2019b)~~(Bresch et al., 2019b). The resulting asset exposure dataset for ~~227~~224 countries is archived in the ETH Research Repository with link: https://doi.org/10.3929/ethz-b-000331316 ~~(Eberenz et al., 2019)~~(Eberenz et al., 2019).

1 Introduction

The modelling of climate risks on a global scale requires globally consistent data representing hazard, vulnerability, and exposure, as defined by the Intergovernmental Panel on Climate Change ~~(IPCC, 2012, 2014) among others. While natural hazard data can be derived from general circulation models, there is a lack of consistent exposure data on a global scale. Exposure data is frequently defined as an inventory of elements at risk from natural hazards (Cardona et al., 2012; UNISDR, 2009). For the modelling of direct economic impacts of disasters, exposure should specifically represent the spatial distribution of physical assets, i.e. buildings and machinery. While aggregate estimates of asset values are available at country level, open data on the spatial distribution of asset values are scarce. Exposure data owned by insurance companies~~(IPCC, 2012, 2014) among others. While natural hazard data can be derived from general circulation models, there is a lack of consistent exposure data on a global scale. Exposure data is frequently defined as an inventory of elements at risk from natural hazards (Cardona et al., 2012; UNISDR, 2009). For the modelling of physical risk as the direct economic impacts of disasters, exposure should specifically represent the spatial distribution of physical asset stock, i.e. buildings and machinery. While aggregate estimates of asset values are available at country level, open data on the spatial distribution of asset values are scarce. Proprietary asset exposure data (e.g. owned by insurance companies) are usually not publicly available.

~~Due to the lack of comprehensive asset inventories, large scale exposure maps are often estimated top-down, using downscaling techniques (De Bono and Mora, 2014; Murakami and Yamagata, 2016). Estimates of total physical asset values can be derived from socio-economic flow measures, such as GDP, since the two indicators exhibit strong correlations (Kuhn and Ríos-Rull, 2016). Annual values of socio-economic flow variables, particularly GDP, are often more readily available than physical asset values. Assuming that human presence and activity are proxies of economic output, downscaling of gross domestic product (GDP) has been based on population combined with land-use, road networks, and locations of airports (Murakami and Yamagata, 2016). While high resolution yearly GDP maps based on this approach were created for academic use (Frieler et al., 2017), there is no recent global high-resolution exposure dataset available for unrestricted use known to us.~~

~~A global exposure data base was produced for the Global Assessment Report 2013 of the United Nations Office for Disaster Risk Reduction (UNISDR), following a downscaling approach (De Bono and Mora, 2014). However, the data base's use beyond the scope of Global Assessment Report is limited, because the data represents urban areas only and was produced from a variety of sources to represent the best estimate of a global exposure data base in 2013. For future quantitative risk assessments, more recent exposure data would be desirable. Reproducing De Bono and Mora's methodology is beyond the scope of most climate impact studies.~~

~~In recent years, the use of nightlight satellite imagery has seen a marked increase in usage in science in general and especially for the estimation of socio-economic indicators (Elvidge et al., 2012; Ghosh et al., 2013; Mellander et al., 2015; Pinkovskiy, 2014). With global satellite images being publicly available and updated regularly, it has been proven to be an useful source of information and is commonly used in scientific contexts for the estimation of unavailable GDP or growth data (Henderson et al., 2012). However, there are some technical limits to the usage of nightlight satellite imagery (Han et al., 2018), especially saturation and blooming. As luminosity can only be distinguished up to a certain brightness, saturation may lead to very bright spots being underrepresented. In the NASA dataset "Earth at Night" (NASA Earth Observatory, 2017), there are 256 shades of brightness, from the minimum zero (no light emission) to the maximum 255. Any pixel brighter than what would entail a value of 255 will also appear at this value (Elvidge et al., 2007).~~

~~Brightness can exude from bright pixels to neighboring pixels, causing the brightness in the latter to be overestimated, leading to blooming. This issue occurs especially in large urban areas and on specific surfaces, such as sand and water (Elvidge et al., 2004; Small et al., 2005). These shortcomings can be mitigated by combining nightlights with other data types: Zhao et al. (2017) enhanced nightlight intensity values with population data to get a more accurate estimation of spatial economic activity in China. They showed that "lit population" (LitPop), the product of nightlight intensity and gridded population count, is a better indicator for economic activity in China than nightlight intensity alone.~~

~~Applying the LitPop approach to spatially explicit exposure estimation on a global level, the present paper documents a globally consistent methodology for the distribution of asset values at high spatial resolution. A LitPop exposure dataset for 227 countries is made available online at the ETH Research Repository (Eberenz et al., 2019). It is suitable to provide the globally consistent exposure base for modelling direct economic disaster impacts. The methodology is published on GitHub as part of the open-source event-based probabilistic impact model CLIMADA (CLIMate ADAptation) (Aznar-Siguan and Bresch, 2019; Bresch et al., 2019a) and archived in the ETH Data Archive (Bresch et al., 2019b).~~

Due to the lack of comprehensive asset stock inventories, large scale asset exposure maps are often estimated top-down, using downscaling techniques (De Bono and Mora, 2014; Gunasekera et al., 2015; Murakami and Yamagata, 2019). On a country aggregate level, estimates of total asset values can be derived from socioeconomic flow measures, such as gross domestic product (GDP), since the two indicators exhibit strong correlations (Kuhn and Ríos-Rull, 2016). Annual values of socioeconomic flow variables, particularly GDP, are often more readily available than asset values. Assuming that human presence and activity are proxies of economic output, downscaling of GDP has been based on geographical population data (Kummu et al., 2018) and on population combined with land-use, road networks, and locations of airports (Murakami and Yamagata, 2019). High resolution yearly GDP maps based on these approaches are publicly available (Geiger et al., 2017;

Kummu et al., 2018). Global asset exposure data were produced for the Global Assessment Report 2013 of the United Nations Office for Disaster Risk Reduction (UNISDR), following a downscaling approach (De Bono and Mora, 2014). However, the data's use beyond the scope of the Global Assessment Report is limited, because the data represents urban areas only and the methodology is not easily reproducible and thus not adaptable. For future quantitative risk assessments, more recent exposure data would be desirable. An alternative methodology to model global asset exposure based on the combination of diverse datasets was presented by Gunasekera et al. (2015). The authors combined data on built-up area, building typologies, and construction cost with sector specific asset data and GDP disaggregated proportional to population density. Unfortunately, the source code and resulting exposure data have not been made publicly available. Reproducing these previously mentioned exposure modelling efforts is beyond the scope of most economic disaster risk assessments and climate change adaptation studies.

In recent years, the use of nightlight intensity from satellite imagery has seen a marked increase in usage in science in general and especially for the disaggregation of socioeconomic indicators (Elvidge et al., 2012; Gettelman et al., 2017; Ghosh et al., 2013; Mellander et al., 2015; Pinkovskiy, 2014; Sutton et al., 2007; Sutton and Costanza, 2002). Being publicly available and updated regularly, global nightlight images have been proven to be a useful source of information and is commonly used in scientific contexts for the estimation of unavailable GDP or growth data (Henderson et al., 2012). However, there are some technical limits to the usage of nightlight satellite imagery (Han et al., 2018), especially saturation and blooming. As luminosity can only be distinguished up to a certain brightness, saturation may lead to very bright spots being underrepresented. In state-of-art nightlight products from the Suomi National Polar-orbiting Partnership's Visible Infrared Imaging Radiometer Suite (VIIRS), there are 256 shades of brightness, from the minimum zero (no light emission) to the maximum 255 (NASA Earth Observatory, 2017; Román et al., 2018). Any pixel brighter than what would entail a value of 255 will also appear at this value (Elvidge et al., 2007). Brightness can exude from bright pixels to neighboring pixels, causing the brightness in the latter to be overestimated, leading to blooming. This issue occurs especially in large urban areas and on specific surfaces, such as sand and water (Elvidge et al., 2004; Small et al., 2005). As a consequence of saturation, socioeconomic indicators scale rather exponentially than linearly with nightlight intensity (Sutton and Costanza, 2002; Zhao et al., 2015, 2017). To counteract the saturation effect, Gettelman (2017) and Aznar-Siguan and Bresch (2019) used exponentially scaled nightlight intensity as a basis for GDP disaggregation for tropical cyclone risk assessments. Saturation and blooming can also be mitigated by combining nightlights with other data types: Sutton et al. (2007) combined the areal extend of lit area with population data to estimate GDP at a subnational level. Zhao et al. (2017) enhanced nightlight intensity values with population data to get a more accurate estimation of spatial economic activity in China. This is based on the observation that there is also an exponential relationship between nightlight intensity and population density. The authors showed that the product of nightlight intensity and gridded population count (called "lit population" by the authors), is a better proxy for economic activity in China than nightlight intensity alone.

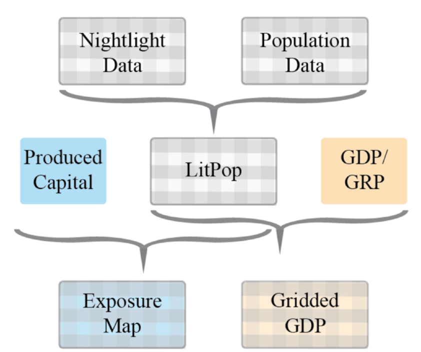
Here, we are using and expanding the "lit population" approach presented by Zhao et al. (2017) to define and implement a globally consistent methodology for asset exposure disaggregation, named LitPop hereafter. This paper presents global gridded asset exposure data, and documents and evaluates the underlying LitPop methodology. The resulting asset exposure dataset for 224 countries is made available online at the ETH Research Repository (Eberenz et al., 2019). It is suitable to provide the globally consistent asset exposure base for modelling physical risks. The methodology is published on GitHub as part of the open-source event-based probabilistic impact model CLIMADA (CLIMate ADAptation) (Aznar-Siguan and Bresch, 2019; Bresch et al., 2019a) and archived in the ETH Data Archive (Bresch et al., 2019b).

Information on input data, methodology, and ~~validation~~the evaluation approach are provided in Section 2. Subsequently, the resulting global ~~LitPop~~asset exposure data ~~is~~are presented and evaluation results shown ~~for selected metropolitan areas (~~in Section 3.~~1), is validated on country level (Section 3.2), and local shortcomings are portrayed in a detailed case study for Mexico City (Section 3.3).~~ The advantages and limitations of the ~~approach~~methodology are discussed in Sections 4~~ and 6~~. Please refer to section 5 for data and code availability.

2 Data & Methods

2.1 Overview

The core functionality of the LitPop ~~exposure approach is to estimate spatially explicit~~ methodology is the spatial disaggregation of national total asset values~~, i.e. the total value of produced capital per geographic grid cell. The work flow of the exposure data modelling is shown in Figure 1:~~ to obtain a gridded asset exposure product. Gridded nightlight ~~data~~intensity (Section 2.2) and gridded population data (Section 2.3) are combined to compute ~~"lit population" (LitPop)~~a digital number at ~~pixel~~grid cell level ~~(Section 2.5). LitPop is then used to obtain gridded physical asset~~. Physical asset stock values ~~by distributing national~~(i.e. produced capital ~~(~~, Section 2.4.1) are then disaggregated proportional to the ~~LitPop value~~digital number per ~~pixel~~grid cell (Section 2.~~6). Likewise, gross domestic product (~~5). This results in the gridded asset exposure dataset presented here. Instead of the physical asset stock, GDP~~,~~ (Section 2.4.2) or gross regional product (GRP, Section 2.4.3) can be distributed to obtain ~~pixel-based~~ GDP per grid cell. Because of a lack of ~~sub-national~~subnational produced capital data, GDP and GRP are used ~~for validation of the underlying downscaling approach~~to evaluate the methodology by assessing the subnational disaggregation skill for varied combinations of the input data, as described in Section 2.~~7~~6. A detailed overview over the input data is provided in Table 1 the disaggregation approach is illustrated in Figure 1.



~~**Figure 1: Work flow of the downscaling methodology: Gridded nightlights and population datasets are combined as LitPop. This is used for the downscaling of produced capital or GDP to estimate gridded exposed assets or gridded GDP respectively.**~~

~~2.2 Satellite nightlight data~~

~~NASA nightlight satellite images (NASA Earth Observatory, 2017) are processed datasets of luminosity by human activity, as recorded by the Satellite Suomi NPP's Visible Infrared Imaging Radiometer Suite (VIIRS). VIIRS marks an distinct improvement over previous technologies, allowing for a greater range of light to be recorded (Carlowicz, 2012). The sun-synchronous satellite passes each place on Earth twice a day, at approximately 1.30 am and pm local time. Nightlight intensity on a scale from 0 to 255 is calculated from the raw measurements, taking into account cloud cover, lunar activity and even the environmental context to isolate luminosity of stable lights (Carlowicz, 2017). The data is provided for 2012 and 2016 at a~~

~~resolution of 15 arcsec, which corresponds to around 500m at the equator. The open-source code developed here can be adapted easily to use other versions and sources of nightlight data. This could be of interest for near-time applications in the future, as NASA aims to eventually provide daily images (Carlowicz, 2017).~~

Input data	**Usage**	**Spatial resolution**	**Reference year**	**Data Source**	**Description**
Gridded nightlights (Lit)	Disaggregation	15 arcsec	2016	NASA's Black Marble nighttime lights (NASA Earth Observatory, 2017; Román et al., 2018)	Section 2.2
Gridded population (Pop)	Disaggregation	30 arcsec (224 countries)	2015	Gridded Population of the World (GPW) (Center for International Earth Science Information Network (CIESIN), 2017)	Section 2.3 and Table S1
Produced capital	Estimation of total asset value	140 countries	2014	World Bank Wealth Accounting (World Bank, 2019a)	Section 2.4.1 and Table S1
GDP-to-wealth ratio	Estimation of total asset value	84 countries	2017	Global Wealth Report (Credit Suisse Research Institute, 2017)	Section 2.4.1 and Table S1
GDP	Estimation of total asset value and evaluation	224 countries	2014*	World Bank Open Data portal (World Bank, 2019b)	Section 2.4.2 and Table S1
GRP	Evaluation	507 regions in 14 countries	2012-2017	Various sources, c.f. Table A1	Section 2.4.3 and Table A1

Table 1: Overview of input dataset, including information on usage, resolution, reference year, data source, and references. The reference year indicates the year for which the data used was provided. *) For GDP, the value of 2014 in current USD was used for 203 countries. For 24 countries without GDP data available for 2014, closest available data points from the years 2000 to 2017 were used instead.

2.2 Satellite nightlight data

The nightlight intensity product used here are nighttime lights of the Black Marble 2016 annual composite of the VIIRS day-night band (DNB) at 15 arcsec resolution (Román et al., 2018), downloaded from the NASA Earth Observatory (2017). The processed datasets of luminosity by human activity based on VIIRS mark an distinct improvement over previous technologies, allowing for a greater range of light to be recorded (Carlowicz, 2012). The sun-synchronous satellite passes each place on Earth twice a day, at approximately 01:30 and 13:30 local time. Nightlight intensity on a scale from 0 to 255 is a variable derived from raw measurements. To isolate luminosity from sustained human activity, the Black Marble nightlight product includes corrections for Lunar artefacts, cloud, terrain, atmospheric, snow, airglow, stray light, and seasonal effects (Carlowicz, 2017; Lee et al., 2014; Román et al., 2018). The data is provided for 2012 and 2016 at a resolution of 15 arcsec, which corresponds to around 500 m at the equator. The open-source code developed here can be adapted easily to use other versions and sources of nightlight data. This could be of interest for near-time applications in the future, as daily nightlight images could be available in the future (Carlowicz, 2017).

2.3 Gridded population data

The Gridded Population of the World (GPW) dataset is a spatially explicit representation of the world's population. It is based on two sets of inputs: non-spatial population data and cartography data. Using census data or population figures by the official national statistics offices, it uniformly distributes the numbers at the smallest available administrative unit to the corresponding cartographic shape, without taking into account any ancillary sources ~~(Doxsey-Whitfield et al., 2015)~~(Doxsey-Whitfield et al., 2015). The data quality for each country strongly depends on the underlying level of availability of population data. For example, for Canada, population data is available down to the fifth subnational administrative unit, of which 493’185 exist. The information ~~there~~for Canada is hence a lot more fine-grained than ~~in~~for instance for Jamaica or Uzbekistan, where population numbers are only recorded at the first subnational administrative unit (Socioeconomic Data and Applications Center (SEDAC), 2017). The level of detail and number of subnational administrative units resolved per country are listed in Table S1. While modelling is kept at a minimum in the GPW dataset, values are inflated or deflated from the latest year with data available to 2000, 2005, 2010, 2015, and 2020 (Center for International Earth Science Information Network (CIESIN), 2017).

~~GPW was selected for this application, because unlike other spatial population datasets, it does not incorporate nightlight satellite data or other auxiliary data sources (Leyk et al., 2019). This allows us to enhance nightlight data with a completely independent dataset. Moreover, it is released under the creative commons license. From GPW, the Population Count v4.10 data at the highest available resolution, 30 arcsec, is used, because it is the closest to NASA's nightlight dataset, in terms of both spatial and temporal resolution.~~

GPW was selected for the LitPop methodology because, unlike other spatial population datasets, it does not incorporate nightlight satellite data or other auxiliary data sources (Leyk et al., 2019). This allows us to enhance nightlight data with a completely independent dataset. Moreover, it is released under the creative commons license. From GPW, the Population Count v4.10 data at the highest available resolution, 30 arcsec, is used, because it is the closest to NASA's nightlight dataset, both in terms of spatial resolution and available time steps.

2.4 Socioeconomic indicators

2.4.1 ~~Produced capital stock~~ Total asset value per country

~~The World Bank’s produced capital stock (World Bank, 2018) is one of the most comprehensive global estimate of the value of manufactured or built assets per country. It has been used as an indicator of exposure to natural disaster in the UNISDR’s Global Assessment Report 2013 (De Bono and Mora, 2014) and produced capital accounts for machinery, equipment, and physical structures (World Bank, 2018). It also includes a fixed scale-up of 24% to account for the value of built-up land.~~

The World Bank’s produced capital stock (World Bank, 2018) is one of the most comprehensive global estimates of the value of manufactured or built assets per country. It has been used as an indicator of exposure to natural disaster in the UNISDR’s Global Assessment Report 2013 (De Bono and Mora, 2014). Produced capital accounts for machinery, equipment, and physical structures (World Bank, 2018). It also includes a fixed scale-up of 24% to account for the value of built-up land.

Produced capital values are currently available for ~~141~~140 countries and 5 time steps: 1995, 2000, 2005, 2010, and 2014 from the World Bank Wealth Accounting ~~(World Bank, 2019a). For target years between 1995 and 2014, produced capital is interpolated linearly. For years outside that range, produced capital is scaled proportionally to the country’s change in GDP.~~(World Bank, 2019a). Per default, the scale-up for built-up land is subtracted, assuming that there is no direct damage to the value of the land itself in the case of disaster. While not universally true, this assumption is based on the focus of the asset exposure data for the purpose of assessing direct impact to tangible structures. For applications considering the impact on the value of land, the linear scale-up can be reapplied before utilization of the asset exposure data.

~~2.4.~~Out of a total of 250 countries we considered for the production of this dataset, produced capital numbers for 2014 are available for 140 countries. For these 140 countries, produced capital for 2014 was used here as total asset value for disaggregation. For additional 87 countries, total asset values were set to non-financial wealth. Non-financial wealth was computed from the country's GDP and the GDP-to-wealth ratio estimates derived from the Credit Suisse Research Institute's Global Wealth Report (Credit Suisse Research Institute, 2017). This approach has previously been followed by Geiger et al. (2018). We compared produced capital and non-financial wealth for 140 countries (Table S1) and found that non-financial wealth can be used as a conservative approximation of produced capital. For 59 of the 87 countries without produced capital data, an average GDP-to-wealth ratio of 1.247 was applied. In summary, the whole dataset contains gridded asset exposure data for a total of 224 countries, ignoring 26 countries and areas due to lack of data. Missing countries and areas (with currently assigned ISO 3166-1 alpha-3 codes) are Aland Islands, Antarctica, Bonaire, British Indian Ocean Territory, Sint Eustatius and Saba, Bouvet Island, Cocos (Keeling) Islands, Christmas Island, Guadeloupe, French Guiana, French Southern Territories, Heard Island and McDonald Islands, Holy See, Kosovo, Libya, Martinique, Mayotte, Pitcairn, Palestine, Reunion, South Georgia and the South Sandwich Islands, South Sudan, Svalbard and Jan Mayen, Syrian Arab Republic, Tokelau, United States Minor Outlying Islands, and Western Sahara. An overview over the utilized data per country, including, produced capital (were available), GDP-to-wealth ratios, and GDP for 2014 is provided in Table S1.

2~~ Gross domestic product~~.4.2 GDP

GDP is a well-established indicator of macroeconomic output. For most countries in the world, annual values are available dating back several decades. ~~National GDP data is retrieved from the World Bank Open Data portal (World Bank, 2019b).~~National GDP data in current USD of 2014 or the nearest available year are retrieved from the World Bank Open Data portal (World Bank, 2019b).

While GDP is not a direct measure of physical asset values, it is used here both ~~to scale~~for scaling asset values in time to fill data gaps and for ~~validation~~the evaluation of the ~~downscaling.~~LitPop methodology. The underlying assumption is that within a country, GDP and wealth are correlated, i.e. a higher GDP value is equivalent to higher asset values. This correlation has been established in empirical studies (Kuhn and Ríos-Rull, 2016).

2.4.3 ~~Gross regional product~~ GRP

The subnational equivalent to GDP is often referred to as GRP. GRP can be used to improve the downscaling of GDP, especially for countries with considerable regional differences. As described ~~below~~ in Section 2.~~7~~6 below, we use GRP data from 14 countries to evaluate the LitPop~~ model's~~ methodology by assessing its skill to ~~predict GRP from~~disaggregate national GDP to a subnational level. As there is no unified data source for GRP, it was gathered manually from government sources and OECD.Stat ~~(Organisation for Economic Co-operation and Development, 2019).~~(Organisation for Economic Co-operation and Development, 2019). The countries used for validation are Australia, Brazil, Canada, Switzerland, China, Germany, France, Indonesia, India, Japan, Mexico, Turkey, USA, and South Africa. The aim of the selection was to include countries from ~~a~~an as wide as possible range of income groups and world regions. Since the selection of countries was limited by the availability of GRP data, the selection has a bias towards ~~developed~~industrialized and ~~emerging economies with~~newly industrialized OECD member states. According to World Bank income groups, these countries include eight countries from the high-income group~~,~~ (World Bank income group 4), four countries from the upper-middle-income group~~,~~ (3), two countries from the lower-middle-income~~,~~ (2), and no countries from the low-income group~~. The income~~ (1). Income groups and data sources per country are listed in Table A1 in the Appendix.

2.5 ~~Computation~~Disaggregation of ~~gridded LitPop~~

~~The computation of gridded LitPop is central to the~~ asset exposure ~~downscaling~~

To produce a high-resolution asset exposure map, the total asset value per country is disaggregated proportional to a function of nightlight luminosity and population count. This approach ~~presented here. The method~~ is closely adapted from the work of Zhao et al. ~~(Naizhuo Zhao et al., 2017).~~(2017). In their paper, historic GDP is ~~downscaled~~disaggregated proportionally to a digital number computed from a multiplicative function of nightlights and population with the aim to make spatial GDP predictions for China. The underlying idea is to enhance brightness values with spatial population data to get a more accurate estimation of spatial economic activity. ~~While the absolute value of LitPop~~The work flow of the asset exposure disaggregation is described here in ~~itself does not bear any interpretable meaning, its relative value~~ detail and illustrated in ~~comparison to the national or subnational sum determines how much of a macroeconomic indicator each pixel receives.~~Figure 1.

In a first step, the two gridded input datasets are interpolated linearly to the same resolution of 30 arcsec~~, or coarser resolution if desired.~~. Then, the combination of the two aforementioned datasets is conducted for each ~~pixel~~grid cell:

$$Lit^n Pop^m{}_{pix} = \left(NL_{pix} + \delta\right)^n \cdot Pop_{pix}{}^m \tag{1}$$

Where the ~~LitPop~~ digital number value ~~$Lit^n Pop^m{}_{pix}$~~ $Lit^m Pop^n{}_{pix}$ per grid cell (*pix*) is computed from the grid cell's nightlight ~~luminosity~~intensity $NL_{pix} \in [0, 255$~~], and~~], population count $Pop_{pix} \in \mathbb{R}^+$~~. The~~ , as well as the exponents $n, m \in \mathbb{N}$ ~~can be adjusted to change the weight of the two input variables (default $n = m = 1$).~~. For all ~~$m > 0$,~~$m > 0$, the added ~~δ~~δ is equal to 1 to ensure that non-illuminated but populated ~~pixels~~grid cells do not get assigned zero value. In the case that nightlight data is used on its own without population data (~~$m = 0$), δ~~$m = 0$), δ is set to 0.

~~2.6 Downscaling~~In a second step, gridded *Lit^m Pop^n* is taken as a relative representation of ~~socioeconomic indicators to LitPop~~

~~The LitPop dataset~~economic stocks at each grid cell. It is used to linearly ~~distribute any known socioeconomic indicator~~disaggregate a total asset values of ~~an administrative unit (i.e.~~ a country ~~or state)~~ to a geographical grid. More precisely, the value of $Lit^m Pop^n{}_{pix}$ relative to the sum of $Lit^m Pop^n$ over all pixels within the boundaries of the country determines how much of a total value is assigned to each grid cell:

$$I_{pix} = I_{tot} \cdot \cancel{\frac{Lit^n Pop^m{}_{pix}}{\sum_i^N \left(Lit^n Pop^m{}_{pix}\right)}} \frac{Lit^n Pop^m{}_{pix}}{\sum_{pix\_i}^N \left(Lit^n Pop^m{}_{pix\_i}\right)} \tag{2}$$

Where ~~I~~I_{pix} denotes the ~~socioeconomic indicator~~asset value per grid cell. The given ~~indicator's total value for the administrative unit I_{tot}~~ value of a country's total asset value I_{tot} is distributed to each ~~pixel I_{pix}~~ grid cell *pix* proportionally to the ~~LitPop~~$Lit^m Pop^n$-share of the ~~pixel. N~~grid cell. N denotes the total number of ~~pixels~~ grid cell (iterator *pix_i*) inside the boundaries of the ~~administrative unit.~~ country.

~~The socioeconomic indicator *I* can represent GDP as in the study of Zhao et al. (2017) and as used here for the validation of the methodology in Section 2.7. For physical risk assessments, an estimation of physical asset value like the World Bank's produced capital stock is distributed.~~

~~2.7 Validation of the Downscaling~~

Changing the exponents *m* and *n* determines with which power the two input variables contribute to the disaggregation function. The exponents *m* and *n* do not only weight relatively between *Lit* and *Pop* but they also determine the contrast in the distribution between all grid cells within a country. The larger the exponent, the more value is concentrated on grid cells with large values of *Lit* or *Pop* respectively. The aim of the evaluation described in Section 2.6 is to compare disaggregation skill of varied combinations of *m* and *n* and select the most adequate combinations for subnational disaggregation.

For the creation of the asset exposure data presented here, *I* represents asset value, i.e. produced capital or non-financial wealth disaggregated per grid cell and *m* and *n* set to 1. For the evaluation of the disaggregation skill of the approach presented in the following section, *I* represents the flow variable GDP instead, as in the study of Zhao et al. (2017).

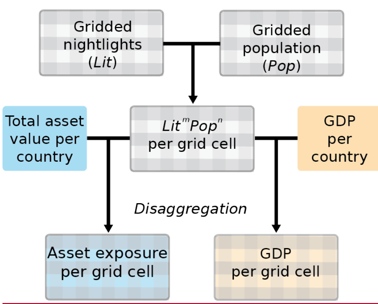


Figure 1: Work flow of the LitPop downscaling: Gridded nightlights (*Lit*) and population (*Pop*) data are combined to compute gridded digital number $Lit^m Pop^n$ (Eq. 1). Then, total asset value per country (i.e. produced capital or non-financial wealth) is disaggregated proportional to $Lit^m Pop^n$ to obtain gridded asset exposure data (Eq. 2). GDP is disaggregated in the same way and compared against reported GRP for the evaluation of the downscaling approach.

2.6 Evaluation

Gridded population and nightlight intensity can both be used as proxies for the spatial distribution of ~~economic activity and wealth.~~asset exposure. Both proxies have limitations: an asset-distribution proportional to population density assumes that physical wealth is distributed equally among the population and that assets are located exactly where people live. As already mentioned in Section 2.3, for many developing countries, gridded population data has a coarse resolution. Nightlight-based models, on the other hand, are mainly limited by saturation and blooming as described in the Introduction. ~~By using LitPop, the product of~~By combining nightlight intensity and population count, we expect to combine their skills while reducing the limitations mentioned above. ~~To validate the performance of the LitPop exposure downscaling, we evaluate its ability to predict the share of subnational administrative units. Due to a lack of data on subnational asset values against which it could be tested, this is done for GDP only. Here, we use gross regional product (GRP) data from 14 countries to evaluate the model's ability to distribute national GDP to subnational regions.~~

The LitPop approach's skill in disaggregating asset exposure cannot be assessed directly due to the lack of reference asset value data on a subnational level. Therefore, GDP and GRP are used instead for an indirect evaluation of the methodology. GDP and GRP are used to assess the subnational disaggregation skill, comparing varying combinations of the exponents *m* and *n* in $Lit^m Pop^n$.

The disaggregation skill is assessed as follows: (i) National GDP is disaggregated to grid level. (ii) The resulting gridded GDP is then re-aggregated for each subnational region (i.e. district, state, or canton) to obtain modelled GRP. (iii) Based on the comparison of normalized modelled and reported reference values of GRP, skill metrics are computed per country. In total, we use reported GRP data for 507 regions in 14 countries to evaluate the model's ability to distribute national GDP to subnational regions.

To ensure comparability of ~~the scores~~skill metrics between different countries, GRP is normalized:

$$nGRP_i = \frac{GRP_i}{GDP} \qquad (3)$$

Where ~~$nGRP_i$[5]~~ $nGRP_i$ denotes the normalized GRP of subnational region ~~i~~i. Given that $GDP = \sum_i^N (GRP_i)$~~;~~, it follows from Equation 3 that $\sum_i^N (nGRP_i) = 1$~~;~~. Here, ~~N~~N is the set of all subnational units in the country.

To assess the ~~model performance~~ disaggregation skill per country, ~~two simple~~three skill ~~scores~~metrics are computed from ~~$nGRP$:~~ $nGRP$:

The Pearson correlation coefficient ~~ρ~~ρ (Equation 4) is computed to measure the linear correlation between the modelled ~~normalized gross regional product $nGRP_{mod}$~~$nGRP_{mod}$ and the reference value ~~$nGRP_{ref}$. ρ~~$nGRP_{ref}$. ρ is computed from the covariance (~~cov~~ cov) and the standard deviations $\sigma_{mod} = \sigma(nGRP_{mod})$ and $\sigma_{ref} = \sigma(nGRP_{ref})$: ~~—~~ $\rho = cov(nGRP_{i,mod}, nGRP_{i,ref})/(\sigma_{mod} \cdot \sigma_{ref}$~~).~~

$$\rho = cov(nGRP_{i,mod}, nGRP_{i,ref})/(\sigma_{mod} \cdot \sigma_{ref}). \qquad (4)$$

The correlation coefficient ~~ρ~~ρ is a widely used ~~score~~metric and straight forward to interpret and communicate: A value of 1 ~~means~~indicates a perfect positive linear correlation between the two variables while a value of 0 ~~means~~indicates that there is no linear correlation. However, ~~ρ~~ρ is no direct measure of the deviations of ~~$nGRP_{mod}$~~ $nGRP_{mod}$ from ~~$nGRP_{ref}$~~ $nGRP_{ref}$ and yields no information regarding the slope of the linear relationship. Therefore, it only represents a potential skill and needs to be evaluated in combination with a measure of the slope. The slope of the linear regression conveys the information, whether there is a systematic over- or underestimation of economically large regions in the disaggregated data. $\beta = \rho \cdot \sigma_{mod}/\sigma_{ref}$ is calculated to complement the analysis: ~~β~~β larger (lower) than 1 implies an overestimation (underestimation) of the GRP of ~~economically strong~~ regions with relatively large GRP and an underestimation (overestimation) of ~~economically small~~ regions ~~in~~with relatively low GRP by the downscaling~~.~~ within one country. Together, ~~ρ~~ρ and ~~β~~β allow for an evaluation of the linear fit between modelled and reference data.

Complementarily, the root-mean-squared fraction (~~RMSF[6]) weights~~RMSF) is a relative error metric, weighting the relative deviation for each region equally, independently of the absolute values. ~~The~~Therefore, RMSF (Equation 5) ~~thus~~ puts equal weight to all subnational administrative units in a country, even if their GRP and thus their absolute difference between ~~prediction~~modelled and reference values are small. A RMSF of 1 indicates perfect fit. A RMSF-value of 2 means that on average, the modelled GRP deviates by a multiplicative factor of 2 from the reference value.

$$RMSF = exp\left(\sqrt{\frac{1}{N}\sum_{i}^{N}\left[\log\left(\frac{nGRP_{i,mod}}{nGRP_{i,ref}}\right)\right]^2}\right) \quad (5)$$

This analysis is applied using varying combinations of nightlight and population data ~~as base~~ for the disaggregation of GDP~~-downscaling: gridded population density (Pop^n), nightlight intensity (Lit^m), and $Lit^m Pop^n$.~~. The resulting skill ~~scores~~metrics are compared for each combination and country.

3 Results

3.1 Global gridded asset exposure

We applied the LitPop methodology with the exponents $m = n = 1$ to compute gridded asset exposure data for 224 countries and areas worldwide (Fig. 2). Total physical asset values of 2014 were disaggregated proportionally to Lit^1Pop^1 to a grid with the spatial resolution of 30 arcsec (approximately 1 km). Total asset values in the dataset sum up to 2.51*10^{14} (251 trillion) current USD of 2014. The 140 countries with produced capital data used as total asset value (c.f. Section 2.4.1), contribute USD 245 trillion (97.6 %) to the total asset exposure. The remaining 84 countries where asset values were estimated from GDP and a GDP-to-wealth ratio instead, contribute the remaining USD 6 trillion. In total, the 224 countries contribute around 99.9% to recorded global GDP. All numbers are based on the national values assembled in Table S1. Data sources are summarized in Table 1.

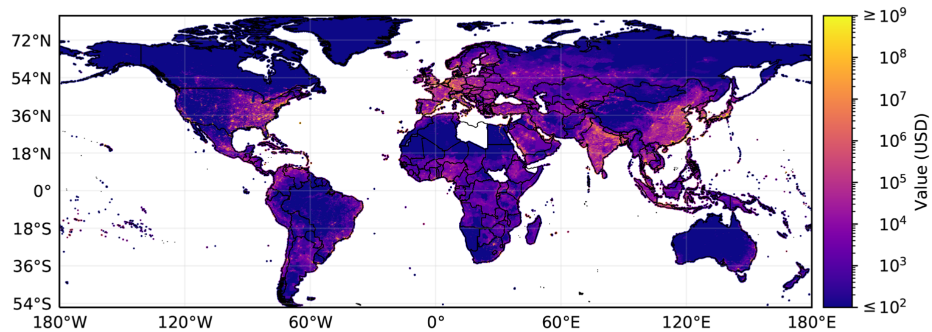


Figure 2: World map showing gridded asset exposure values scaled to a resolution of 600 arcsec. The actual resolution of the underlying gridded data is 30 arcsec (~1 km). To obtain this dataset, national total asset values were disaggregated proportional to the distribution of Lit^1Pop^1 for 224 countries and areas. 26 countries and areas without data are left blank, including Libya, South Sudan, and Syria. The colormap is logarithmic and cropped at USD 100 (lower bound) and USD 1,000,000,000 (upper bound).

In the following subsections, the LitPop methodology is evaluated both quantitatively and qualitatively: The results of the quantitative assessment of disaggregation skill introduced in Section 2.6 are presented in Section 3.2, providing justification for the selected combination of the exponents *m* and *n* for the global dataset. Differences between asset exposure distribution based on Lit^1, Pop^1, and Lit^1Pop^1 are shown by example of detail maps of two metropolitan areas (Section 3.3). Finally, limitations of the LitPop methodology are discussed by the example of GDP disaggregation in Mexico (Section 3.4).

3.2 Evaluation

To evaluate the performance of the LitPop methodology, we compute and compare the disaggregation skill in regards to GDP for varying exponents *m* and *n* in $Lit^m Pop^n$ (Eq. 1 and 2). Here, we show the comparison based on 14 countries with a total of 507 regional GRP data points available. The 14 countries make up 67% (USD 168 trillion) of the total dataset's exposure and 64.5% (USD 52 trillion) of global GDP in 2014. Ten combinations of *m* and *n* are assessed: Lit^1Pop^1, Lit^1, Lit^2, Lit^3, Lit^4 , Lit^5, Pop^1, Pop^2, Lit^2Pop^1, and Lit^3Pop^1. These exponent combinations were selected based on examples in the literature and then explored iteratively, stopping at combinations with decreased skill compared to lower order combinations. For each country and exponent combination, the median and the spread of three skill metrics are compared: ρ, β, and RMSF (Fig. 3 and Tables A2 and A3).

For ρ (Fig. 3a), Lit^1Pop^1 shows the best overall median of ρ (0.94) with the lowest interquartile range (IQR) of 0.09. The IQR is used here as a measure of variability of the skill metrics, as it signifies the difference between the 25th and the 75th percentile of the resulting skill metric. The same holds for β of Lit^1Pop^1 (median=1.03, IQR=0.12, Fig. 3b). In contrast, β is on average well below 1 for combinations exclusively based on *Lit* (i.e. Lit^m). A value of β below 1 indicates an underestimation of the GRP of economically larger regions compared and an overestimation of smaller regions. This can possibly be attributed to the saturation problem of nightlight intensity data, given that economically large regions usually accommodate more metropolitan areas where saturation occurs the most. This interpretation is supported by the relatively low values attributed to London and Mumbai metropolitan areas ~~In this section, the skill of the LitPop exposure downscaling is examined both qualitatively and quantitively. Since most exposed values are concentrated in urban areas (De Bono and Mora, 2014), exposure maps of two metropolitan areas are discussed with a focus on saturation, blooming, and resolution in Section 3.1. The results of the quantitative validation introduced in Section 2.7 are presented in Section 3.2. Finally, limitations of the LitPop-methodology are discussed by the example of Mexico.~~

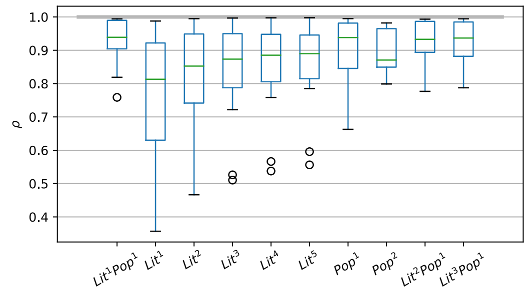
~~3.1 Metropolitan~~by Lit^1 shown in Section 3.3.

For purely population-based disaggregation, we found a median of β below 1 for $Pop^1$and well above 1 for Pop^2 (Fig. 3b). This suggests that disaggregation proportional to Pop^1 underestimates the asset values in urban agglomerations, while it is overestimated by Pop^2. For the metric RMSF, Pop^1 (median=1.37, IQR=0.37) and Lit^4 (median=1.64, IQR=0.36) perform best, while Lit^1Pop^1 has a median RMSF of 1.67 and an IQR of 1.29 (Fig. 3c).

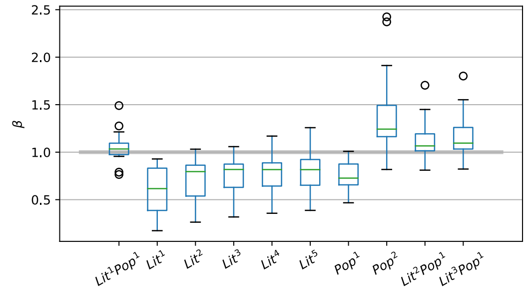
Within the set of combinations exclusively based on *Lit* (n=0), the skill metrics β and RMSF perform best for Lit^4 (Fig. 3b,c), with median ρ improving for larger values of m, however changing little from Lit^4 to Lit^5 (Fig. 3a).

Based on the comparison of the disaggregation skill with varying exponent *m* and *n*, there are two candidates for the most adequate functionality: Lit^1Pop^1 (best ρ and β) and Lit^4 (best RMSF and best performance for n=0). The skill metrics of linear regression, ρ and β, give a better representation of the disaggregation skill for the absolute values than RMSF which is based on the relative deviation per data point. Prioritizing a better distribution of total values over relative performance, we conclude that Lit^1Pop^1 can be considered the most adequate combination of *Lit* and *Pop* for the subnational downscaling of GDP. For countries with a lack of highly resolved population data, alternative datasets could be produced based on Lit^4 alone.

a)



b)



c)

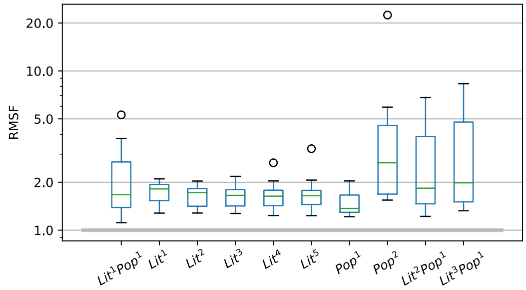
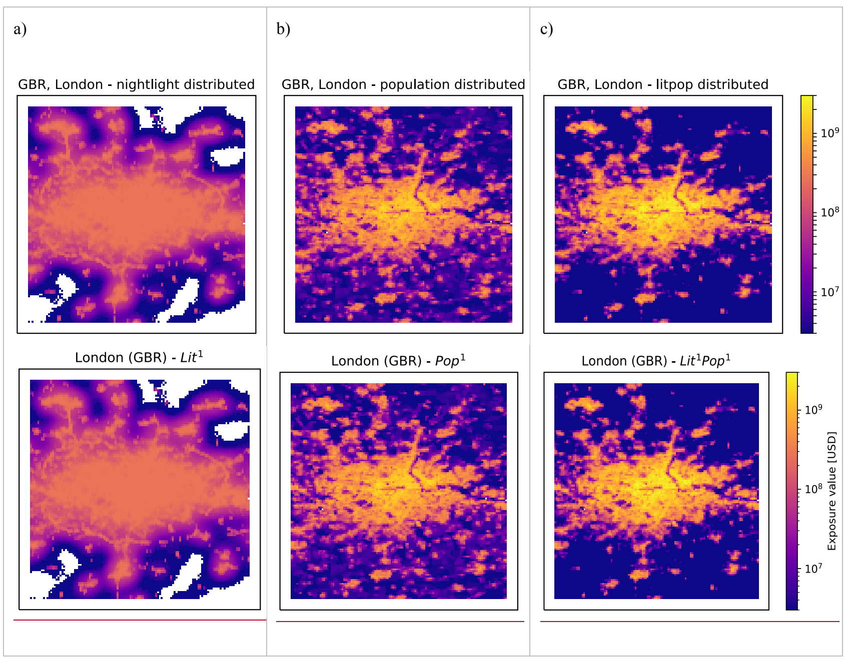


Figure 3: Box plots showing the skill metrics ρ (a), β (b), and RMSF (c) for variations of $Lit^m Pop^n$. The metric value of 1, indicating perfect skill, is demarcated by the solid grey line. The plots are based on data from 14 countries and show the median (green), the 1st and 3rd quartile (IQR, blue box), data points outside the IQR but not more than 1.5*IQR distance from the median (black whiskers), and outliers (black circles). RMSF is plotted on a logarithmic scale.

Underlying metric values per country are listed in Table A2. Median and IQR per skill metric and combination of exponents are shown in Table A3.

3.3 Detailed maps for metropolitan areas

Saturation and blooming in nightlight intensity data cause ~~exposure maps~~disaggregation based on nightlights alone to misrepresent actual value distribution, especially in urban areas. This can be seen in Figure ~~2~~4, showing maps based on ~~nightlight intensity~~Lit^1 (a), ~~population count~~Pop^1 (b) and ~~LitPop~~Lit^1Pop^1 (c~~), which is the product of the first two datasets.~~). London (top row) and Mumbai (bottom), two large metropolitan areas, were chosen as examples. Comparable maps for Mexico City and New York are shown in Figure A1 in the Appendix.



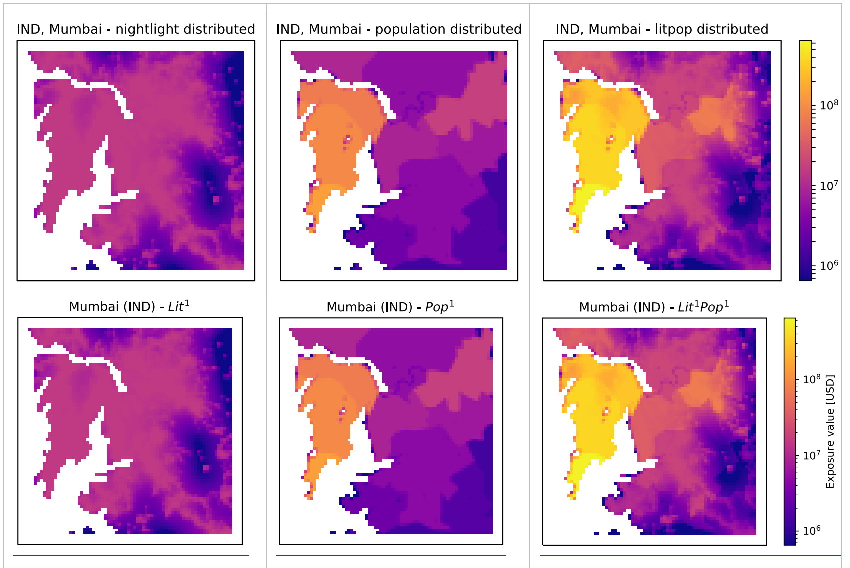


Figure ~~2: National produced capital as~~4: Maps of ~~2014.~~disaggregated asset exposure value. Values are spatially distributed proportional to nightlight intensity of 2016 (Lit^1, a), population count as of 2015 (Pop^1, b), and the product of both (~~LitPop~~Lit^1Pop^1, c) for metropolitan areas in the United Kingdom (GBR) and India (IND). The maps are restricted to the wider metropolitan areas of London (0.6°W-0.4°E; 51-52°N) and Mumbai (72-73.35°E; 18.8-19.4°N) respectively. The ~~log-normal~~ colorbar shows asset exposure values in current USD of 2014 per pixel of approximately 1 km^2.

~~The value distribution based on nightlight intensity (Fig. 2a~~The general exposure value level in the metropolitan areas shown in Fig. 4 are largest for Lit^1Pop^1 (Fig. 4c), highlighting a larger concentration of values in urban areas with this approach. The value distribution based on Lit^1 (Fig. 4a) does not show many details within the urban area. This effect is partially caused by saturation: the light radiation in the depicted areas is of such high intensity, that the nightlight data does not offer any way to distinguish different levels of human activity. We can also observe the blooming effect, with the luminosity of bright parts crowding out to neighboring pixels, causing them to appear brighter than their underlying light sources would warrant. This latter effect can be particularly illustrated over the Thames river and Bow Creek in the northeastern part of London: The unpopulated river area is resolved ~~in the population data~~by Pop^1 (Fig. ~~2b~~4b top) but not by ~~the nightlights~~Lit^1 (Fig. ~~2a~~4a top). By taking population density into account, the ~~LitPop~~ Lit^1Pop^1 dataset enhances contrast and detail in urban areas (Fig. ~~2b~~4b, c). In addition, bright objects can be over-represented by ~~nightlight intensity~~Lit^1: In Figure ~~2a~~4a (top), the M25 London Orbital Motorway around London clearly stands out, with some pixels even at the same value as in central London.

As seen in the case of Mumbai, the ~~LitPop~~ Lit^1Pop^1 based asset exposure map of the metropolitan area in Figure ~~2c (top~~4c (bottom) shows much higher total values than those based on nightlights or population alone. This means that for ~~LitPop,~~Lit^1Pop^1, a larger proportion of the national produced capital of India is attributed to the metropolitan area of Mumbai~~. Whether the subnational distribution of values is more accurate for LitPop than for the other two datasets, is evaluated in Section 3.2~~ as compared to Lit^1 and Pop^1 alone.

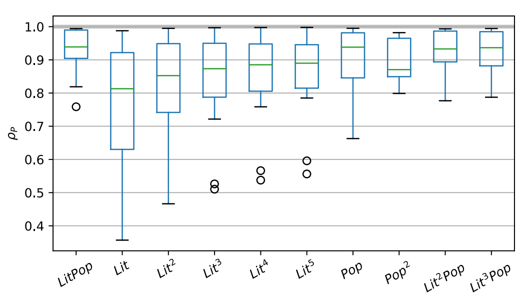
3.~~2 Validation~~4 Example Mexico

The ~~downscaling within countries is validated by comparing the downscaled and reported~~ skill metrics for the subnational ~~GDP with three quantitative methods.~~disaggregation of GDP in the country Mexico shows low values of ρ compared to most other countries for all tested values of m and n (ρ=0.76 for Lit^1Pop^1, c.f. Table A2a). The ~~Pearson correlation coefficient ρ, linear slope parameter β,~~example of Mexico is presented here to illustrate limitations and ~~root-mean-squared fraction RMSF per country are shown in Tables A2. To compare the overall performance~~uncertainties of the ~~different methods, median and spread of the scores are compared in~~disaggregation approach. Figure ~~3 and Table A3. As for the linear regression, $LitPop$ shows the highest overall median correlation coefficient of 0.94 with the lowest interquartile range (IQR[7]) of 0.09. The same holds for the slope parameter of $LitPop$ ($median = 1.03, IQR = 0.12$). In contrast, the slope parameter is on average well below 1 for all exponents of Lit. A slope below 1 indicates an underestimation of the GRP of economically larger regions compared and an overestimation of smaller regions. This can possibly be attributed to the saturation problem of nightlight intensity data, given that economically large regions usually accommodate more metropolitan areas where saturation occurs the most. This interpretation is supported by the relatively low values attributed to London and Mumbai metropolitan areas as observed in Figure 2a. For population-based methods, we found a median slope below 1 for Pop and well above 1 for Pop^2. This suggests that population-based distribution underestimates the asset values in urban agglomerations, while it is overestimated by Pop^2.~~

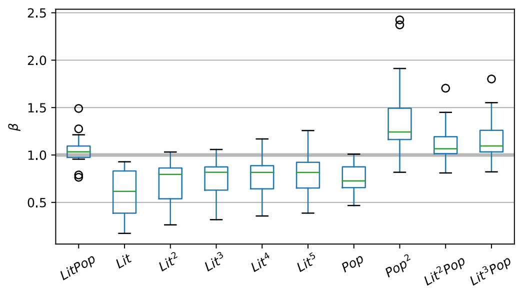
~~Figure 3c~~5 shows the ~~RMSF. RMSF is the average multiplicative error between two datasets, giving the same weight to all data point independently of absolute value. A RMSF-value of 2 means that on average, the~~ data behind the evaluation for Mexico, i.e. modelled ~~GRP deviates by a multiplicative factor of 2 from the~~ and reference ~~value. For this score, Pop ($median = 1.37, IQR = 0.37$) and Lit^4 ($median = 1.64, IQR = 0.36$) perform best, while $LitPop$ has a median RMSF of 1.67 and an IQR of 1.29.~~

~~Based on these results, we conclude that $LitPop$ is the most an adequate combination of Lit and Pop for the subnational downscaling of GDP.~~

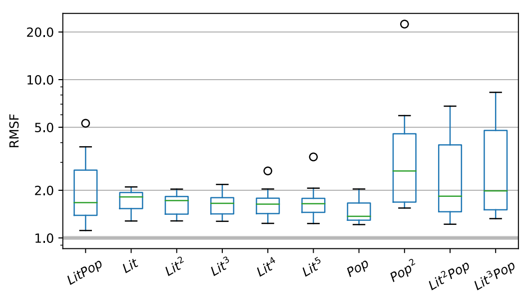
~~a)~~



~~b)~~



~~c)~~



~~**Figure 3: Box plots showing the Pearson correlation coefficient ρ (a), linear regression slope β (b), and root mean squared fraction RMSF (c) for variations of Lit^{n}Pop^m. The best score of 1 is demarcated by the solid grey line. The plots are based on data from 14 countries and show the 1st, 2nd and 3rd quartile (box), 1.5*interquartile range (black whiskers), and outliers (black circles). RMSF is plotted on a logarithmic scale. Numbers are shown in Table A3.**~~

~~**3.3 Example Mexico**~~

~~In the validation in Section 3.2, Mexico shows low correlation ρ compared to most other countries. Figure 4 shows the modelled and reference normalized gross regional product (~~*nGRP*~~)~~ for all 32 districts of Mexico. The corresponding plot data can be found in Table ~~S.1~~S2 as supplementary material. While the LitPop~~-~~ methodology ~~works~~performs well for most of the ~~smaller~~ districts with relatively low GRP, it fails to reproduce ~~the~~reference *nGRP* for the main (capital) metropolitan region ~~with~~ consisting of the districts México and Mexico City~~. Exposure~~ (Distrito Federal).

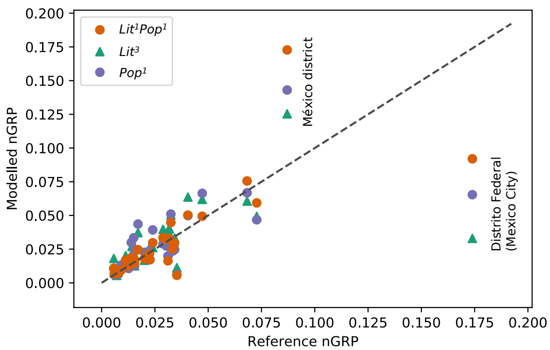
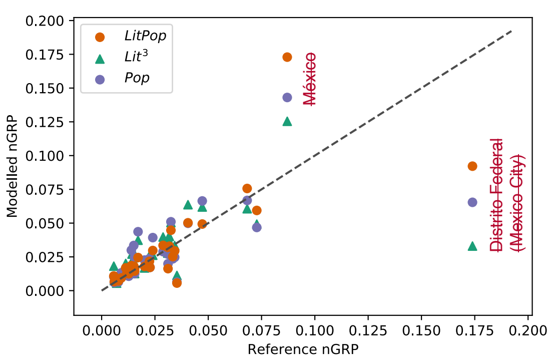


Figure 5: Normalized gross regional product (*nGRP*) for the 32 districts of Mexico. Reference values are shown on the horizontal axis and modelled values on the vertical axis.

The two districts with the largest GRP of the highly centralized country are Distrito Federal (Mexico City district) with a reference *nGRP* of 17.4% and México district (8.7%), surrounding the Distrito Federal. Asset exposure maps of the metropolitan region are shown in Figure A1 in the Appendix.



~~**Figure 4: Normalized gross regional product (nGRP) for the 32 districts of Mexico. Reference values are shown on the horizontal axis and modelled values on the vertical axis.**~~

~~The two economically largest districts of the highly centralized country are Distrito Federal (Mexico City) with a reported *nGRP* of 17.4% and the surrounding México (8.7%). The LitPop-based downscaling~~ The disaggregation of GDP underestimates *nGRP* for Mexico City district while overestimating the value for México ~~(Fig. 4). The overestimation of México's GRP~~ for all evaluated combinations of ~~*Lit*~~*m* and ~~*Pop*~~*n* (*nGRP* for Lit^1Pop^1, Lit^3, and Pop^1 are shown in Figure 5). The overestimation of México district's *nGRP* indicates that the district has ~~a high~~an over-proportional nightlight ~~luminosity~~intensity and population ~~density~~count compared to a relatively low ~~economic output. This phenomenon could be an artefact of Mexico City's urban sprawl (de la Luz Hernández-Flores et al., 2017): There is probably a lot of housing and infrastructure in suburban México that is used by a population that works in the city and thus contributes to the GRP of Mexico City. Following this speculative interpretation, downscaling with LitPop might be more appropriate for physical assets (i.e. produced capital) than for GDP. Since no subnational breakdown of produced capital stock is available, we cannot test this hypothesis.~~reference *nGRP*. Both districts combined sum up to modelled *nGRP* values of 11.2 to 17,6% for Lit^m, 20.8% for Pop^1, and 26.5% for Lit^1Pop^1 (Table S2), the latter agreeing well to a combined reference *nGRP* of 26.1%.

~~Using reference GRP as an intermediate downscaling layer in the case of Mexico would increase the estimated exposure in the Mexico City and decrease the exposure in the surrounding district of México. While this would obviously improve the downscaling for GDP, it might not be adequate for the distribution of physical assets. Further studies could use subnational asset values to examine whether the correlation between GDP and asset values is stronger than the correlation between LitPop and asset value. Where subnational asset values exist, they can be used as intermediate downscaling layers for physical assets.~~

4 Discussion

The LitPop methodology allows for the creation of globally consistent and spatially highly resolved estimates of gridded ~~physical~~ asset exposure value. According to Pittore et al. ~~(2017)~~(2017), efforts towards improving exposure data should aim at global consistency, continuous integration of new data and methods, and a careful validation of models and data. Here, we will discuss the advantages and limitations of the LitPop methodology with regard to the following key criteria: Global consistency, ~~predictive~~disaggregation skill, scalability and flexibility, openness, replicability and reproducibility, and low entry threshold:

Global consistency. Based on ~~global~~ globally available input data, the LitPop methodology ~~performs well~~was applied across countries from different continents and income groups~~ without any customization.~~. While the presented asset exposure dataset is not complete, it provides data for 224 countries contributing 99.9% of global GDP. Therefore, LitPop-based asset exposure data can be used as a basis for globally comparable economic risk assessments. ~~In order to improve downscaling for countries with large regional differences, a subnational breakdown of GDP in the form of GRP data can be used as an intermediate downscaling layer wherever available. As~~However, the ~~case of Mexico City (Section 3.3) suggests,~~ evaluation of the ~~link between LitPop and asset value might be stronger than~~ of the ~~link between LitPop and GDP~~methodology's disaggregation skill presented here is limited to an assessment of disaggregation skill for 14 OECD countries. It should be noted that due to lack of data we were not able to evaluate the method's performance for ~~countries in income group 1.~~low income countries (World Bank income group 1). Therefore, the application of the asset exposure data for local assessments in countries within low income groups should be treated with caution. Another caveat to global consistency is the fact that the quality and resolution of the underlying population dataset varies between countries~~. This is discussed below~~, as discussed in greater detail in the next paragraph. As a consequence of these limitations, asset exposure data should be validated against local data before application for local risk assessments, especially in low income countries.

~~*Predictive skill.* LitPop shows high skill in predicting subnational economic output based on the downscaling of national GDP in the 14 countries analyzed in detail. Although the skill of downscaling exposure cannot be validated directly, the high skill of LitPop for GDP downscaling recommends this method also for exposure downscaling. The evaluation of correlation coefficients and linear regression slope showed that LitPop distributes GDP better than other multiplicative combinations of nightlight and population data. In most of the evaluated countries, there is a large number of economically relatively small regions compared to few large ones. While the linear regression parameters are more sensitive to outliers (i.e. how good the fit is for regions with a large GRP), a low value of RMSF indicates that the smaller regions' GRPs were reproduced well by the model. For RMSF, pure population data performs best on average. Depending on the application, population data could be considered as an alternative basis for downscaling. However, the resolution of population data varies between countries. For high resolution risk assessments, the exact distribution of light sources as highlighted by nightlight data allows for an increase in spatial precision. Based on our results, we recommend LitPop for physical risk assessment because it combines the advantages of both input data types and mitigates their disadvantages, i.e. resolution, saturation and blooming. For countries without a high-resolution distribution of population in the gridded dataset, an exposure map based on~~ ~~$Lit^n Pop^m$~~ ~~is equivalent to one based on~~ ~~Lit^n~~ ~~alone. For more locally refined risk assessments, in countries with coarsely resolved population information, we advise to use a higher exponent of nightlights instead, i.e.~~ ~~$n \geq 3$~~~~. Additionally, LitPop could be combined or masked with other auxiliary data, such as road networks, land cover (Murakami and Yamagata, 2016), or mobile phone cell antenna density (Brönnimann and Wintzer, 2018).~~

~~*Scalability and flexibility.* Subject to data availability, the LitPop exposure model can be used to estimate the distribution of physical asset values for any target year at a wide range of resolutions. Our used data sources cater for resolutions up to 30 arcsec. While the GPW dataset provides population data for the previous two decades, the NASA nightlight images are currently only available for 2012 and 2016. The methodology includes a scaling of exposure data proportional to current GDP for years without any data available. The model can be adapted to a variety of applications by an appropriate choice of the macroeconomic indicator: The World Bank's produced capital data is set as the default total asset value per country. Alternatively, GDP can be used as an estimator of economic output. GDP multiplied by a factor derived from the country specific income group can also be used to estimate asset values (Aznar-Siguan and Bresch, 2019). Since the CLIMADA repository is open-source, the LitPop methodology can easily be amended to include alternative data sources and versions of both gridded nightlight, population, asset base or other socioeconomic indicators to expand the repertory of the top-down exposure data model. The LitPop methodology was developed to provide a globally consistent exposure base for large-scale disaster risk modelling. While it could be used for other applications as well, the limitations of its scope should be noted: The top-down approach implemented here does not account for differences in infrastructure types and vulnerability. In addition, gridded data may cause poor scoping of areas most vulnerable to risk, or those with more exposed population. Thus, the applicability for local-based applications and detailed socio-economic risk assessments is limited by the top-down nature of our methodology. Especially for risk assessments with a local focus as well as in countries with low resolution of population data, we would advise to use more local-based approaches and bottom-up methods for identifying and analyzing the vulnerability component.~~

Assessment of disaggregation skill. For the gridded exposure dataset presented here, the LitPop methodology is used to disaggregate total asset values. Due to a lack of subnational reference asset values, the LitPop methodology's performance for the downscaling of asset stock values could not be evaluated directly. The assessment of disaggregation skill was instead based on the flow variables GDP and GRP. Given a correlation between stocks and flows within each country, this approach represents an indirect evaluation of the methodology for asset exposure downscaling. Evaluating 14 countries, we found that the LitPop methodology generally performs well in disaggregating GDP to subnational level. The skill metrics ρ and β showed that Lit^1Pop^1 distributes GDP better to the subnational level than the other combinations of nightlight and population data assessed. For RMSF, Pop^1 and Lit^4 perform best on average. We selected Lit^1Pop^1 as a basis for the disaggregated asset exposure dataset presented here. This decision is based on two considerations: (1) Giving ρ and β priority over RMSF because they are measures of absolute deviation between variables (as compared to RMSF that is a measure of relative deviation per data point); and (2) the fact that Lit^1Pop^1 combines the advantages of both input data types and mitigates their disadvantages, i.e. with regard to saturation, blooming, and detail. For countries without a high detail level in the population data available, asset exposure based on Lit^mPop^n is more or less equivalent to one based on Lit^m alone. For regional application in these countries, evaluation results suggest that disaggregation proportional to Lit^4 could distribute asset values best in the absence of detailed population data.

Scalability and flexibility. Subject to data availability, the LitPop methodology can be used to estimate the distribution of physical asset values for any target year at a wide range of resolutions. The data sources used here cater for resolutions up to 30 arcsec. While the GPW dataset provides population data for the previous two decades, the NASA nightlight images are currently only available for 2012 and 2016. The methodology includes a scaling of exposure data proportional to current GDP for years without any data available. The methodology can potentially be adapted to a variety of applications by an appropriate choice of the socioeconomic indicator that is disaggregated: The World Bank's produced capital data is used here as the default total asset value per country. Alternatively, GDP can be used as an estimator of economic output. GDP multiplied by a factor derived from the country specific income group can also be used to estimate asset values (Aznar-Siguan and Bresch, 2019; Geiger et al., 2017). This was done for countries without produced capital numbers available. Since the CLIMADA repository is open-source, the LitPop methodology can be amended to include alternative data sources and versions of both gridded nightlight, population, and total asset values, or other socioeconomic indicators to expand and update the asset exposure data. The LitPop methodology was developed to provide globally consistent asset exposure data for global-scale physical risk modelling. While it could be used for other applications as well, the limitations of its scope should be noted: The LitPop methodology does not account for differences in infrastructure types and vulnerability. In addition, gridded data may cause poor scoping of areas most vulnerable, or those with more exposed population. The example of Mexico (Section 3.4) illustrates the limitations of the LitPop methodology when it comes to the disaggregation of GDP within a metropolitan area: While the disaggregation of GDP proportional to Lit^1Pop^1 nicely reproduces the summed *nGRP* of the metropolitan area, the methodology fails to reproduce the distribution of *nGRP* between the two districts that make up the metropolitan area. Therefore, the use of the asset exposure data for local applications should be treated with care. The use for local or sector specific applications is limited without the addition of sector specific datasets. For risk assessments with a local focus as well as in countries of low income, we would advise to use more local approaches and bottom-up methods for identifying and analyzing the vulnerability component. Additionally, the asset exposure data could be further refined by including auxiliary data, such as road networks and land cover (Geiger et al., 2017; Murakami and Yamagata, 2019), or mobile phone cell antenna density (Brönnimann and Wintzer, 2018). In order to include sector specific assets not represented by the LitPop methodology, i.e. power plants or mines in unpopulated areas, additional sector specific asset inventories should be included (Gunasekera et al., 2015). For a globally consistent approach, sectoral data should however be included with caution, as such datasets are prone to regional or national biases.

Openness, replicability, and low entry threshold. The LitPop methodology was developed in the programming language Python 3 and published on the code hosting service GitHub as well as in a permanent repository (c.f. Section 5). The CLIMADA repository is developed open-source and makes use of open-access data to enable unrestricted use for applications also beyond academia. ~~The~~ Next to the dataset provided, the LitPop-module can be used both to apply the computed asset exposure data ~~directly~~for direct application in event-based risk ~~assessment~~assessments with CLIMADA or to export gridded asset exposure data to standard formats for use in other applications. While ~~*LitPop*~~Lit^1Pop^1 is the default~~, any multiplicative combination of *Lit* and *Pop*~~ , Lit^mPop^n with custom exponents can be chosen as a ~~downscaling function~~basis for disaggregation. The documentation of CLIMADA is hosted on Read the Docs (https://climada-python.readthedocs.io/en/stable/). It includes an interactive tutorial of CLIMADA and the LitPop module (https://climada-python.readthedocs.io/en/stable/tutorial/climada_entity_LitPop.html), with guidance on how to compute and export LitPop based asset exposure data.

5 Data and code availability

~~LitPop~~Asset exposure data at a resolution of 30 arcsec for ~~227~~224 countries, ~~and~~as well as normalized ~~*Lit*~~Lit^1 and ~~*Pop*~~Pop^1 for the 14 countries ~~highlighted in this study is~~used for evaluation are archived in the ETH Research Repository with link:

https://doi.org/10.3929/ethz-b-000331316 ~~(Eberenz et al., 2019)~~(Eberenz et al., 2019). The LitPop methodology is openly available as a module of CLIMADA ~~(Bresch et al., 2019a)~~(Bresch et al., 2019a) at GitHub under the GNU GPL license ~~(GNU Operating System, 2007).~~(GNU Operating System, 2007). CLIMADA v1.2.0 was used for this publication, which is permanently available at the ETH Data Archive with link: http://doi.org/10.5905/ethz-1007-226 ~~(Bresch et al., 2019b)~~(Bresch et al., 2019b). The scripts reproducing the published dataset, as well as all figures in the present publication and the main results are published in the CLIMADA-papers repository on GitHub with link: https://github.com/CLIMADA-project ~~(Aznar-Siguan et al., 2019)~~(Aznar-Siguan et al., 2019).

6 Conclusion

The open-source LitPop ~~exposure~~ methodology was developed to provide a geographical distribution of physical asset exposure values that can be used to model first-order economic impacts of weather and climate ~~and weather~~ events~~.~~ and other natural disasters. It integrates publicly available data sources to calculate ~~area-based economical~~gridded asset exposure estimates. The global consistency, flexibility and openness, and the integration in the CLIMADA repository offers value for manifold use cases for ~~top-down~~ economic disaster risk modelling and climate change adaptation studies. However, the methodology could not be evaluated directly against subnational asset data and the evaluation based on GDP was limited to 14 OECD countries. Therefore, the asset exposure data is not suitable for applications with a local or sector-specific focus without further validation. Future research and development could focus on the integration of higher resolved population data and other ancillary data sources as they ~~get~~become available globally~~, and validation~~. Validation against subnational asset value and empirical asset stock inventories yields the potential to evaluate and further improve the accuracy of ~~the top-down~~asset exposure downscaling ~~against bottom-up data~~, both for global and regional applications. Regional validation could further inform the choice of the most appropriate downscaling functionality for different income groups and world regions.

Appendix A

Country	Regions	Income Group	Data Source	Reference year
Australia	8	4	Australian Bureau of Statistics, http://www.abs.gov.au/AUSSTATS/abs@.nsf/DetailsPage/5220.02016-17?OpenDocument	2016
Brazil	27	3	OECD.Stat, https://stats.oecd.org/	2015
Canada	14	4	OECD.Stat, https://stats.oecd.org/	2016
Switzerland	26	4	Swiss Federal Statistical Office, https://www.bfs.admin.ch/bfs/en/home/statistics/national-economy/national-accounts/gross-domestic-product-canton.assetdetail.6369918.html	2014
China	31	3	National Bureau of Statistics China, http://data.stats.gov.cn/english/easyquery.htm?cn=E0103	2015
Germany	16	4	Statistische Ämter des Bundes und der Länder, https://web.archive.org/web/20110717065817/http://www.statistik-portal.de/Statistik-Portal/en/en_jb27_jahrtab65.asp	2017
France	101	4	Eurostat, http://ec.europa.eu/eurostat/web/regions/data/database	2015
Indonesia	33	2	OECD.Stat, https://stats.oecd.org/	2012
India	30	2	Open Government Data Platform India, https://data.gov.in/catalog/capita-state-domestic-product-current-prices#web_catalog_tabs_block_10	2013/14
Japan	47	4	Cabinet Office Government of Japan, http://www.esri.cao.go.jp/jp/sna/data/data_list/kenmin/files/contents/main_h26.html	2014
Mexico	32	3	National Institute of Statistics and Geography of Mexico, https://www.inegi.org.mx/sistemas/bie/?idserPadre=10200070#D10200070	2016
Turkey	81	3	OECD.Stat, https://stats.oecd.org/	2014
USA	52	4	US Bureau of Economic Analysis, https://www.bea.gov/data/gdp/gdp-state	2016
South Africa	9	3	OECD.Stat, https://stats.oecd.org/	2013

Table A1: List of countries used for validation with the number of regions on the administrative level 1, the World Bank income group 2016, and ~~gross regional product (GRP)~~GRP data source with URLs as accessed in January 2019. The income groups are: low income (1), lower middle income (2), upper middle income (3) and high income (4). In total, GRP data for 507 regions in 14 countries were used.

~~ρ~~ρ	AUS	BRA	CAN	CHE	CHN	DEU	FRA	IDN	IND	JPN	MEX	TUR	USA	ZAF
~~*LitPop*~~ Lit^1Pop^1	0.99	0.98	0.99	0.94	0.93	0.90	0.92	0.90	0.82	0.93	0.76	0.99	0.98	0.99
~~*Lit*~~ Lit^1	0.92	0.92	0.99	0.81	0.95	0.96	0.37	0.75	0.81	0.59	0.36	0.53	0.76	0.85
~~*Lit²*~~ Lit^2	0.93	0.96	0.99	0.89	0.96	0.94	0.47	0.79	0.82	0.73	0.47	0.66	0.78	0.95
~~*Lit³*~~ Lit^3	0.94	0.96	1.00	0.91	0.95	0.93	0.51	0.83	0.83	0.79	0.53	0.72	0.79	0.97
~~*Lit⁴*~~ Lit^4	0.94	0.97	1.00	0.93	0.95	0.92	0.54	0.85	0.84	0.82	0.57	0.76	0.80	0.97
~~*Lit⁵*~~ Lit^5	0.94	0.97	1.00	0.93	0.95	0.91	0.56	0.87	0.84	0.84	0.60	0.79	0.81	0.97
~~*Pop*~~ Pop^1	0.99	0.96	1.00	0.97	0.85	0.98	0.84	0.80	0.79	0.92	0.66	0.98	0.98	0.92
~~*Pop²*~~ Pop^2	0.97	0.97	0.98	0.81	0.82	0.88	0.86	0.86	0.80	0.96	0.85	0.96	0.86	0.97
~~*Lit²Pop*~~ Lit^2Pop^1	0.99	0.99	0.99	0.89	0.90	0.86	0.92	0.90	0.87	0.94	0.78	0.99	0.98	0.99
~~*Lit³Pop*~~ Lit^3Pop^1	0.99	0.99	0.99	0.86	0.89	0.84	0.93	0.89	0.88	0.95	0.79	0.99	0.98	0.98

~~Table A2a: Pearson correlation coefficient ρ for~~Table A2a: Comparison of ρ for ten exponent combinations and 14 countries: Australia (AUS), Brazil (BRA), Canada (CAN), Switzerland (CHE), China (CHN), Germany (DEU), France (FRA), Indonesia (IDN), India (IND), Japan (JPN), Mexico (MEX), Turkey (TUR), United States of America (USA), and South Africa (ZAF). Best fit would mean ρ=1. Linear correlation is statistically significant with a p-value lower than 0.05 for all shown countries and combinations.

β	AUS	BRA	CAN	CHE	CHN	DEU	FRA	IDN	IND	JPN	MEX	TUR	USA	ZAF
Lit^1Pop^1	1.02	0.79	1.10	1.07	1.05	1.01	0.96	1.21	0.96	1.28	0.76	1.49	1.01	1.07
Lit^1	0.82	0.55	0.90	0.67	0.93	0.89	0.22	0.76	0.84	0.33	0.22	0.17	0.57	0.54
Lit^2	0.82	0.61	0.96	0.77	1.03	0.89	0.32	0.83	0.82	0.52	0.32	0.26	0.62	0.87
Lit^3	0.82	0.63	0.99	0.84	1.06	0.88	0.38	0.86	0.82	0.64	0.38	0.32	0.65	1.05
Lit^4	0.82	0.64	1.01	0.89	1.07	0.86	0.41	0.88	0.81	0.73	0.42	0.36	0.66	1.17
Lit^5	0.82	0.64	1.02	0.93	1.07	0.85	0.44	0.90	0.81	0.80	0.45	0.39	0.67	1.26
Pop^1	1.01	0.66	1.01	0.87	0.68	0.92	0.47	0.77	0.84	0.66	0.55	0.61	0.88	0.65
Pop^2	1.23	0.97	1.21	1.16	0.82	1.01	2.42	1.40	1.19	1.91	1.26	2.37	1.52	1.40
Lit^2Pop^1	1.03	0.81	1.12	1.12	1.04	0.99	1.09	1.26	1.01	1.45	0.82	1.70	1.04	1.22
Lit^3Pop^1	1.03	0.82	1.13	1.15	1.03	0.96	1.16	1.29	1.04	1.55	0.86	1.80	1.06	1.32

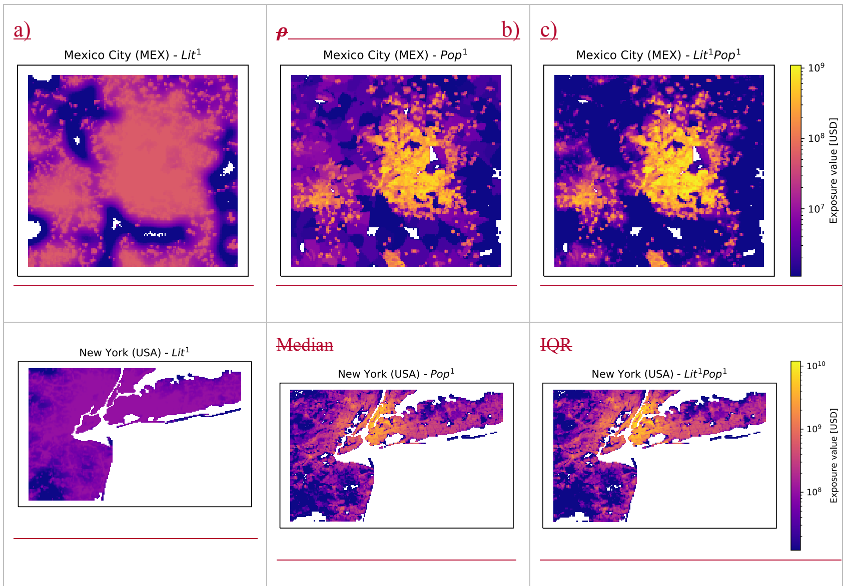
Table A2b: Comparison of β for ten exponent combinations and 14 countries: Australia (AUS), Brazil (BRA), Canada (CAN), Switzerland (CHE), China (CHN), Germany (DEU), France (FRA), Indonesia (IDN), India (IND), Japan (JPN), Mexico (MEX), Turkey (TUR), United States of America (USA), and South Africa (ZAF). Best fit would mean ~~ρ = 1.~~(β=1). Linear correlation is statistically significant with a p-value lower than 0.05 for all shown countries and combinations.

RMSF	AUS	BRA	CAN	CHE	CHN	DEU	FRA	IDN	IND	JPN	MEX	TUR	USA	ZAF
Lit^1Pop^1	1.31	1.54	1.80	2.70	1.37	1.44	1.93	5.30	2.61	2.86	1.55	3.76	1.37	1.11
Lit^1	1.28	1.93	1.69	1.74	1.50	1.44	1.89	2.00	2.10	1.52	1.93	2.03	1.94	1.58
Lit^2	1.28	1.83	1.51	1.85	1.42	1.36	1.68	1.86	2.03	1.41	1.77	1.77	1.81	1.37
Lit^3	1.32	1.80	1.48	2.18	1.40	1.38	1.63	1.81	2.02	1.47	1.69	1.68	1.77	1.27
Lit^4	1.34	1.79	1.49	2.65	1.40	1.40	1.63	1.79	2.04	1.58	1.64	1.64	1.77	1.24
Lit^5	1.37	1.78	1.53	3.25	1.40	1.42	1.66	1.79	2.06	1.70	1.60	1.63	1.77	1.23
Pop^1	1.27	1.72	1.29	1.36	1.48	1.32	1.38	2.04	1.73	1.21	1.69	1.59	1.32	1.28
Pop^2	1.67	1.73	3.50	3.18	1.61	1.64	4.73	5.93	4.01	5.34	1.81	22.4	2.12	1.54
Lit^2Pop^1	1.37	1.53	2.07	4.18	1.40	1.60	2.41	6.80	3.00	4.16	1.53	6.36	1.44	1.22
Lit^3Pop^1	1.41	1.53	2.27	5.74	1.41	1.69	2.75	7.64	3.23	5.29	1.52	8.31	1.50	1.32

Table ~~A2b: Linear slope β~~A2c: Comparison of RMSF for ten exponent combinations and 14 countries: Australia (AUS), Brazil (BRA), Canada (CAN), Switzerland (CHE), China (CHN), Germany (DEU), France (FRA), Indonesia (IDN), India (IND), Japan (JPN), Mexico (MEX), Turkey (TUR), United States of America (USA), and South Africa (ZAF). ~~Best fit would mean β = 1. Linear correlation is statistically significant with a p-value lower than 0.05 for all shown countries and combinations.~~Best fit would mean RMSF=1.

	ρ		β		**RMSF**	
	Median	IQR	Median	IQR	Median	IQR
Lit^1Pop^1	0.94	0.09	1.03	0.12	1.67	1.29
Lit^1	0.81	0.29	0.62	0.44	1.82	0.40
Lit^2	0.85	0.21	0.80	0.32	1.72	0.41
Lit^3	0.87	0.16	0.82	0.24	1.65	0.38
Lit^4	0.89	0.14	0.82	0.24	1.64	0.36
Lit^5	0.89	0.13	0.82	0.27	1.65	0.33
Pop^1	0.94	0.14	0.73	0.22	1.37	0.37
Pop^2	0.87	0.12	1.24	0.33	2.65	2.87
Lit^2Pop^1	0.93	0.09	1.07	0.18	1.83	2.41
Lit^3Pop^1	0.94	0.10	1.10	0.23	1.98	3.27

Table A3: Comparison of three skill metrics measuring the fit between modelled and reference nGRP. The table shows the median and IQR over 14 countries computed from the data in Tables A2a-c. Perfect fit would mean a value of one for each metric.

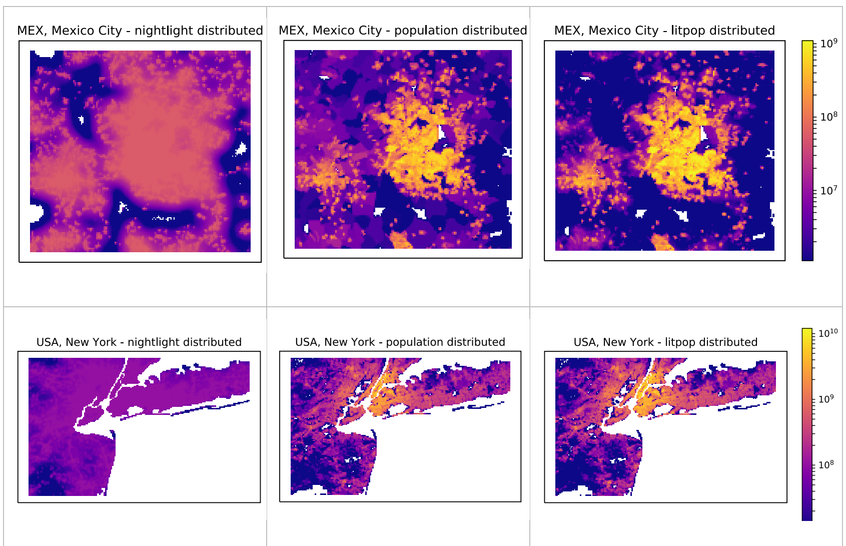


~~*LitPop*~~	~~0.94~~	~~0.09~~	~~1.03~~	~~0.12~~	~~1.67~~	~~1.29~~
~~*Lit*~~	~~0.81~~	~~0.29~~	~~0.62~~	~~0.44~~	~~1.82~~	~~0.40~~
~~Lit^2~~	~~0.85~~	~~0.21~~	~~0.80~~	~~0.32~~	~~1.72~~	~~0.41~~
~~Lit^3~~	~~0.87~~	~~0.16~~	~~0.82~~	~~0.24~~	~~1.65~~	~~0.38~~
~~Lit^4~~	~~0.89~~	~~0.14~~	~~0.82~~	~~0.24~~	~~1.64~~	~~0.36~~
~~Lit^5~~	~~0.89~~	~~0.13~~	~~0.82~~	~~0.27~~	~~1.65~~	~~0.33~~
~~*Pop*~~	~~0.94~~	~~0.14~~	~~0.73~~	~~0.22~~	~~1.37~~	~~0.37~~
~~Pop^2~~	~~0.87~~	~~0.12~~	~~1.24~~	~~0.33~~	~~2.65~~	~~2.87~~

~~0.18~~**Figure A1: Maps of disaggregated asset exposure value. Values are spatially distributed proportional to nightlight intensity of 2016 (*Lit*[1], a), population count as of 2015 (*Pop*[1], b), and the product of both (*Lit*[1]*Pop*[1], c) for Mexico City (MEX) and New York (USA). The maps are restricted to the wider metropolitan areas of Mexico City (99.8-98.6°W; 18.9-20°N) and New York (74.6- 73°W; 40- 41°N) respectively. The colorbar shows asset exposure values in current USD for 2014.**

~~Lit^3Pop~~	~~0.94~~	~~0.10~~	~~1.10~~	~~0.23~~	~~1.98~~	~~3.27~~

~~**Table A3: Comparison of three skill scores measuring the fit between modelled and reference normalized gross regional products. Median and interquartile range (IQR) over 14 countries are computed from the data in Tables A2a-c. The scores are Pearson correlation coefficient ρ, slope β, and the root-mean-squared fraction RMSF. Perfect fit would mean a value of one for each score.**~~



~~**Figure A1: National produced capital distributed proportional to nightlight intensity (left column), population count (middle), and LitPop (right) for the Mexico (MEX) and USA. The maps are restricted to the wider metropolitan areas of Mexico City (99.8-98.6°W; 18.9-20°N) and New York (74.6- 73°W; 40- 41°N) respectively. The log-normal colorbar shows exposure values in USD for 2014.**~~

Author contributions

DS, SE, and DNB developed the method collaboratively. The programming code was written by DS, TR, and SE. Validation and visualization was done by TR and SE. SE prepared the manuscript with contributions from all co-authors.

Competing interests

The authors declare that they have no conflict of interest.

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